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VOLUME SEGMENTATION
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UNIVERSITY OF MALAYA
SESSION 2002/2003

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A graduation exercise submitted to the Faculty of Computer Science and Information Technology, University of Malaya.

In partial fulfillment of the requirement for the Bachelor of Computer Science degree.

Acknowledgement

Firstly, I would like to take this opportunity to express my appreciation to my thesis supervisor Mr. Woo Chaw Seng for his guidance and advices in the process of preparing this project. Secondly, I would like to thank Miss. Mangalam Sankupellay for being a project moderator.

I would like to thank my teammate, especially to Mohd Tharmezy and Ahmad Azarizal for their encouragement and cooperation during the process of developing this project.

Last but not least, I wish to express my heartiest appreciation to my family and all who give a contribution directly or indirectly until I finished my project. Let god bless all of you. Thank you.

Abstract

Segmentation is in many cases the bottleneck when trying to use radiological image data in many clinically important applications as radiological diagnosis, monitoring, radiotherapy and surgical planning. While manual segmentation is often regarded as a gold standard, its usage is not acceptable in some clinical situations.

A new breed of methodologies improves on the shortcoming of the traditional methods. These new solution are describing as intelligent and encompass fuzzy logic and neural network. Fuzzy logic and Neural network are complimentary and can be combined to form a neuro-fuzzy approach. This overcomes the shortcoming of both and can provide a robust and intelligent methodology for image analysis.

This documentation is about the implementation of neuro-fuzzy approach using Fuzzy Hopfield Neural Network (FHNN) algorithm for the segmentation process of MR image data sets.

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CHAPTER ONE

INTRODUCTION

1.1 Topic Overview

Technology transfer from different areas has dramatically changed the art of medical diagnosis and therapy in the past few years. While a considerable part of this development is already indispensable in today's daily clinical routine, current results represent only the first milestones on the way of medicine into the information age. The permanent quest for more effective and less invasive treatment transformed the widespread integrated use of information technology, image guidance and intelligent instrumentation to centrally important key components of patient care which offer a huge and up to now only partially understood and explored potential for computer aided medicine.

Medical imaging is the most important source of anatomical and functional information which are indispensable for up-to-date diagnosis and therapy. Current radiological units provide huge amount of high resolution three-dimensional spatial (and in many cases also temporal) data, which cannot be effectively processed and utilized with traditional visualization and image interpretation techniques. Computerized medical image analysis and visualization algorithms are therefore of fundamental importance to make possibly full use of the information buried in the acquired enormous flood of image data.

The increasing availability of computing power as well as appropriate modeling and description methods recently enabled rapid development in:

- Physically based simulation of complex medical systems and the underlying biological processes to support therapy planning as well as medical education and training in general;
- Quantitative image analysis for disease and therapy monitoring, including morphological measurement methods for the characterization of biological shape.

Segmentation is in many cases the bottleneck when trying to use radiological image data in many clinically important applications as radiological diagnosis, monitoring, radiotherapy and surgical planning. While manual image segmentation is often regarded as a gold standard, its usage is not acceptable in some clinical situations. In some applications such as computer assisted neurosurgery or radiotherapy planning e.g., a large number of organs have to be identified in the radiological data sets.

Delineation of organ boundaries is also necessary in various types of clinical studies, where the correlation between morphological changes and therapeutically actions or clinical diagnosis has to be analyzed. In order to get statistically significant results, a large number of data sets have to be segmented. For such applications manual segmentation becomes questionable not only because of the amount of work, but also with regard to the poor reproducibility of the results.

Magnetic resonance imaging (MRI) is an imaging technique used primarily in medical settings to produce high quality images of the inside of the human body. MRI is based on the principles of nuclear magnetic resonance (NMR), a spectroscopic technique used by scientists to obtain microscopic chemical and physical information about molecules.

The technique was called magnetic resonance imaging rather than nuclear magnetic resonance imaging (NMRI) because of the negative connotations associated with the word nuclear in the late 1970's. MRI started out as a tomographic imaging technique, that is it produced an image of the NMR signal in a thin slice through the human body. MRI has advanced beyond a tomographic imaging technique to a volume imaging technique.

The level of detail we can see is extraordinary compared with any other imaging modality. MRI is the method of choice for the diagnosis of many types of injuries and conditions because of the incredible ability to tailor the ex\m to the particular medical question being asked. By changing exam parameter, the MRI system can cause tissue in the body to take on different appearances. This is very useful to the radiologist in determining if something seen is normal or abnormal. MRI system can also image flowing blood in virtually any part of the body.

Today as increasingly more sophisticated biological imaging problems are tackled, there is a greater need for improved solutions, unbounded by the limitations of traditional methods.

A new breed of methodologies improves on the shortcoming of the traditional methods. These new solutions are describing as 'intelligent' and encompass fuzzy logic and neural network. To interpret real images and thus gain an understanding of them, it is important to be able to recognize and analyze objects, features and patterns within such images. Image recognition requires a multitude of pre-processing stages before it can be initiated.

Fuzzy logic has become popular in recent years for its ability to handle approximate rules and model complex system. Fuzzy logic allows image processing technique to be developed using flexible rules defined in natural human language.

Neural network (NN) let a system learn and adapt for purpose of identification, approximation or classification. The main advantage of neural network is their model free nature. Through learning and adapting from raw data alone, NN can estimate almost any unknown function and are well suited to handle variation in data caused for example by noise.

Fuzzy logic and neural network are complimentary, and can be combined to form a neuro-fuzzy approach. This overcomes the shortcomings of both, and can provide a robust and intelligent methodology for image analysis.

This chapter will define a target and work involve in this project. Section 1.2 explains the project objectives. Section 1.3 explains about project scope and finally section 1.4 explains the project schedule.

1.2 Project Objectives

The objectives of these work is as follow;

1. To study about segmentation process using neuro-fuzzy technique on MR imaging data set.
2. To segment and model the specific human anatomy of interest from transverse MR images.
3. To use a neuro-fuzzy technique in segmentation process.

I hope by the end of this work, this system will fulfill all objectives stated above.

1.3 Project Scope

The work involves is to design and implementation of segmentation and extraction of anatomy of interest from magnetic resonance (MR) images. This system will allow user to view a segmented part of anatomy for each slice.

The segmentation process will carried out using neuro-fuzzy technique through a few slices of MR images data sets. The part that has been segmented from the image will be extract in a binary image.

There are some limitations that this system cannot do. The final product of segmented part of anatomy from the MRI data sets are presented in a from of black and white or binary image. This is adequate to measure the quality of segmentation process.

Secondly, this system cannot provide a nice interface for user because the major target in this system is to implement an intelligent technique to solve a real problem.

1.4 Project Schedule

Figure below describe the project schedule based on the system development methodology. The project schedule is important to ensure that all the respective development phases are implemented in an appropriate period of time. It basically drafts out the duration required and by each phase.

Table 1.1 : Project Schedule

No.	Task	Start Date	End Date
1.	Literature Review	1/4/2003	30/4/2003
2.	Requirement Analysis	8/4/2003	7/5/2003
3.	System Design	15/4/2003	14/5/2003
4.	System development	15/5/2003	31/7/2003
5.	Integration testing	1/8/2003	31/8/2003
6.	System testing	22/8/2003	30/9/2003
7.	Documentation	8/4/2003	30/9/2003

This schedule also presented in a Gant chart at the next page.

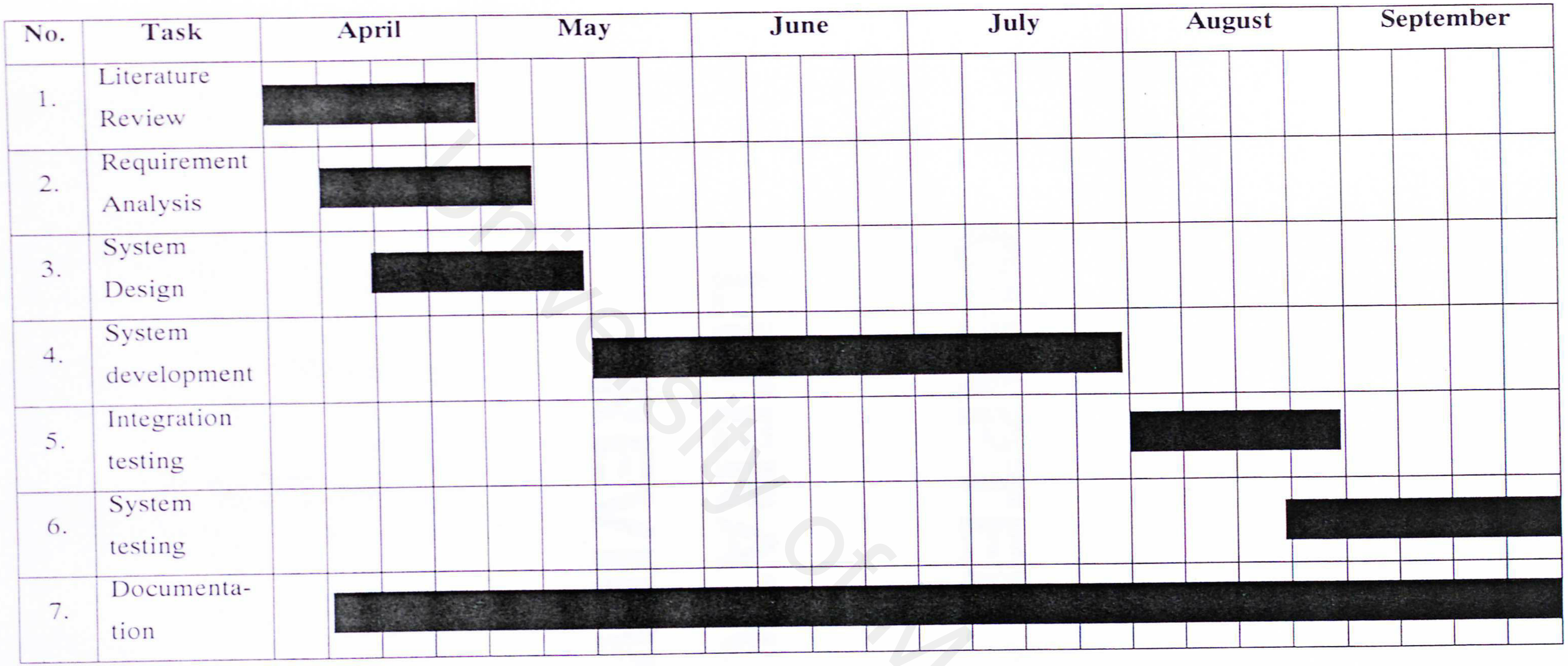


Figure 1.1 : Gant Chart for System Development

CHAPTER TWO

LITERATURE REVIEW

2.1 Study on Magnetic Resonance Imaging (MRI)

2.1.1 Introduction to MRI

An MRI is a very effective tool for detecting brain tumors, signs of a previous stroke, bleeding, abnormalities in the brain and spinal cord, bone cancer, and injuries to the bones, joints, and soft tissues. It is also used to diagnose neurological diseases such as multiple sclerosis, as well as heart disease and eye, nose, and ear disorders. MRI is needed when x-rays cannot provide adequate pictures of the structure being studied, or when repeated scans are needed and there is concern over excessive exposure to radiation [1].

2.1.2 A Brief History about MRI

Felix Bloch and Edward Purcell, both of whom were awarded the Nobel Prize in 1952, discovered the magnetic resonance phenomenon independently in 1946. In the period between 1950 and 1970, NMR was developed and used for chemical and physical molecular analysis. In 1971 Raymond Damadian showed that the nuclear magnetic relaxation times of tissues and tumors differed, thus motivating scientists to consider magnetic resonance for the detection of disease. In 1973 the x-ray-based computerized tomography (CT) was introduced by Hounsfield. This date is important to the MRI timeline because it showed hospitals were willing to spend large amounts of money for medical imaging hardware.

Magnetic resonance imaging was first demonstrated on small test tube samples that same year by Paul Lauterbur. He used a back projection technique similar to that used in CT. In 1975 Richard Ernst proposed magnetic resonance imaging using phase and frequency encoding, and the Fourier Transform. This technique is the basis of current MRI techniques. A few years later, in 1977, Raymond Damadian demonstrated MRI of the whole body. In this same year, Peter Mansfield developed the echo-planar imaging (EPI) technique. This technique will be developed in later years to produce images at video rates (30 ms / image). Edelstein and coworkers demonstrated imaging of the body using Ernst's technique in 1980.

A single image could be acquired in approximately five minutes by this technique. By 1986, the imaging time was reduced to about five seconds, without sacrificing too much image quality. The same year people were developing the NMR microscope, which allowed approximately 10 mm resolution on approximately one cm samples. In 1987 echo-planar imaging was used to perform real-time movie imaging of a single cardiac cycle. In this same year Charles Dumoulin was perfecting magnetic resonance angiography (MRA), which allowed imaging of flowing blood without the use of contrast agents. In 1991, Richard Ernst was rewarded for his achievements in pulsed Fourier Transform NMR and MRI with the Nobel Prize in Chemistry. In 1993 functional MRI (fMRI) was developed. This technique allows the mapping of the function of the various regions of the human brain. Six years earlier many clinicians thought echo-planar imaging's primary applications was to be in real-time cardiac imaging. The development of fMRI opened up a new application for EPI in mapping the regions of the brain responsible for thought and motor control.

In 1994, researchers at the State University of New York at Stony Brook and Princeton University demonstrated the imaging of hyperpolarized 129Xe gas for respiration studies. MRI is clearly a young, but growing science. [2]

2.1.3 MRI : How it Work?

The human body is made up of untold billions of atoms, the fundamental building blocks of all matter. The nucleus of an atom spins, or precesses, on an axis. You can think of the nucleus of an atom as a top spinning somewhere off its vertical axis.

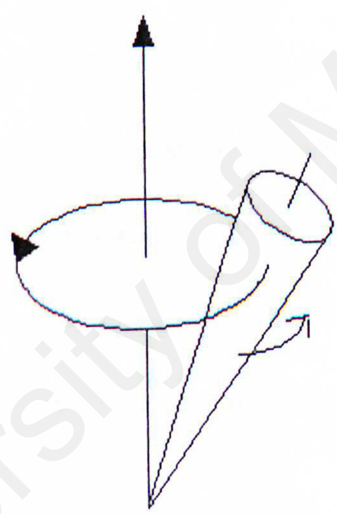


Figure 2.1: A top that is spinning slightly off the vertical axis is precessing about the vertical axis.

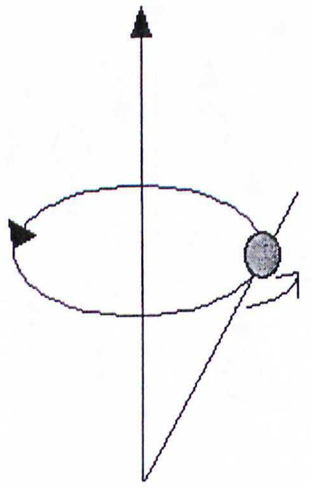


Figure 2.2 : A hydrogen atom precesses about a magnetic field.

There are many different types of atoms in the body, but for the purposes of MRI, we are only concerned with the hydrogen atom. It is an ideal atom for MRI because its nucleus has a single proton and a large magnetic moment. The large magnetic moment means that, when placed in a magnetic field, the hydrogen atom has a strong tendency to line up with the direction of the magnetic field.

Inside the bore of the scanner, the magnetic field runs straight down the center of the tube in which we place the patient. This means that if a patient is lying on his or her back in the scanner, the hydrogen protons in his or her body will line up in the direction of either the feet or the head. The vast majority of these protons will cancel each other out -- that is, for each one lined up toward the feet, one toward the head will cancel it out. Only a couple of protons out of every million are not canceled out. This doesn't sound like much, but the sheer number of hydrogen atoms in the body gives us what we need to create wonderful images.

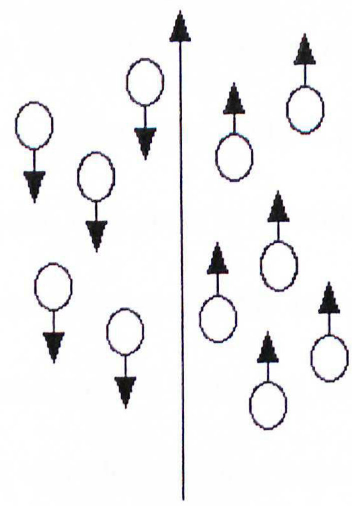


Figure 2.3: Magnetic Field In MR Scanning Process

All of the hydrogen protons will align with the magnetic field in one direction or the other. The vast majority cancel each other out, but, as shown here, in any sample there is one or two "extra" protons.

Inside the magnetic field, these billions of extra protons are lined up and ready to go. MRI machine applies an RF (radio frequency) pulse that is specific only to hydrogen. The system directs the pulse toward the area of the body we want to examine. The pulse causes the protons in that area to absorb the energy required to make them spin, or precess, in a different direction. This is the "resonance" part of MRI. The RF pulse forces them (only the one or two extra unmatched protons per million) to spin at a particular frequency, in a particular direction. The specific frequency of resonance is called the Larmour frequency and is calculated based on the particular tissue being imaged and the strength of the main magnetic field.

These RF pulses are usually applied through a coil. MRI machines come with many different coils designed for different parts of the body: knees, shoulders, wrists, heads, necks and so on. These coils usually conform to the contour of the body part being imaged, or at least reside very close to it during the exam. At approximately the same time, the three gradient magnets jump into the act. They are arranged in such a manner inside the main magnet that when they are turned on and off very rapidly in a specific manner, they alter the main magnetic field on a very local level. What this means is that we can pick exactly which area we want a picture of. In MRI we speak of "slices." Think of a loaf of bread with slices as thin as a few millimeters -- the slices in MRI are that precise. We can "slice" any part of the body in any direction, giving us a huge advantage over any other imaging modality. That also means that you don't have to move for the machine to get an image from a different direction -- the machine can manipulate everything with the gradient magnets.

When the RF pulse is turned off, the hydrogen protons begin to slowly (relatively speaking) return to their natural alignment within the magnetic field and release their excess stored energy. When they do this, they give off a signal that the coil now picks up and sends to the computer system. What the system receives is mathematical data that is converted, through the use of a Fourier transform, into a picture that we can put on film. That is the "imaging" part of MRI [3].

2.1.4 Visualization Process

Most imaging modalities use injectable contrast, or dyes, for certain procedures. MRI is no different. What is different is the type of contrast we use, how it works and why we use it.

The contrast or dye materials used in X-ray and CT scan work in the same way because both areas use X-rays (ionizing radiation). These agents work by blocking the X-ray photons from passing through the area where they are located and reaching the X-ray film. This results in differing levels of density on the X-ray/CT film. These dyes have no direct physiologic impact on the tissue in the body. The contrast used in MRI is fundamentally different.

MRI contrast works by altering the local magnetic field in the tissue being examined. Normal and abnormal tissue will respond differently to this slight alteration, giving us differing signals. These varied signals are transferred to the images, allowing us to visualize many different types of tissue abnormalities and disease processes better than we could without the contrast [3].

2.1.5 MRI Structure

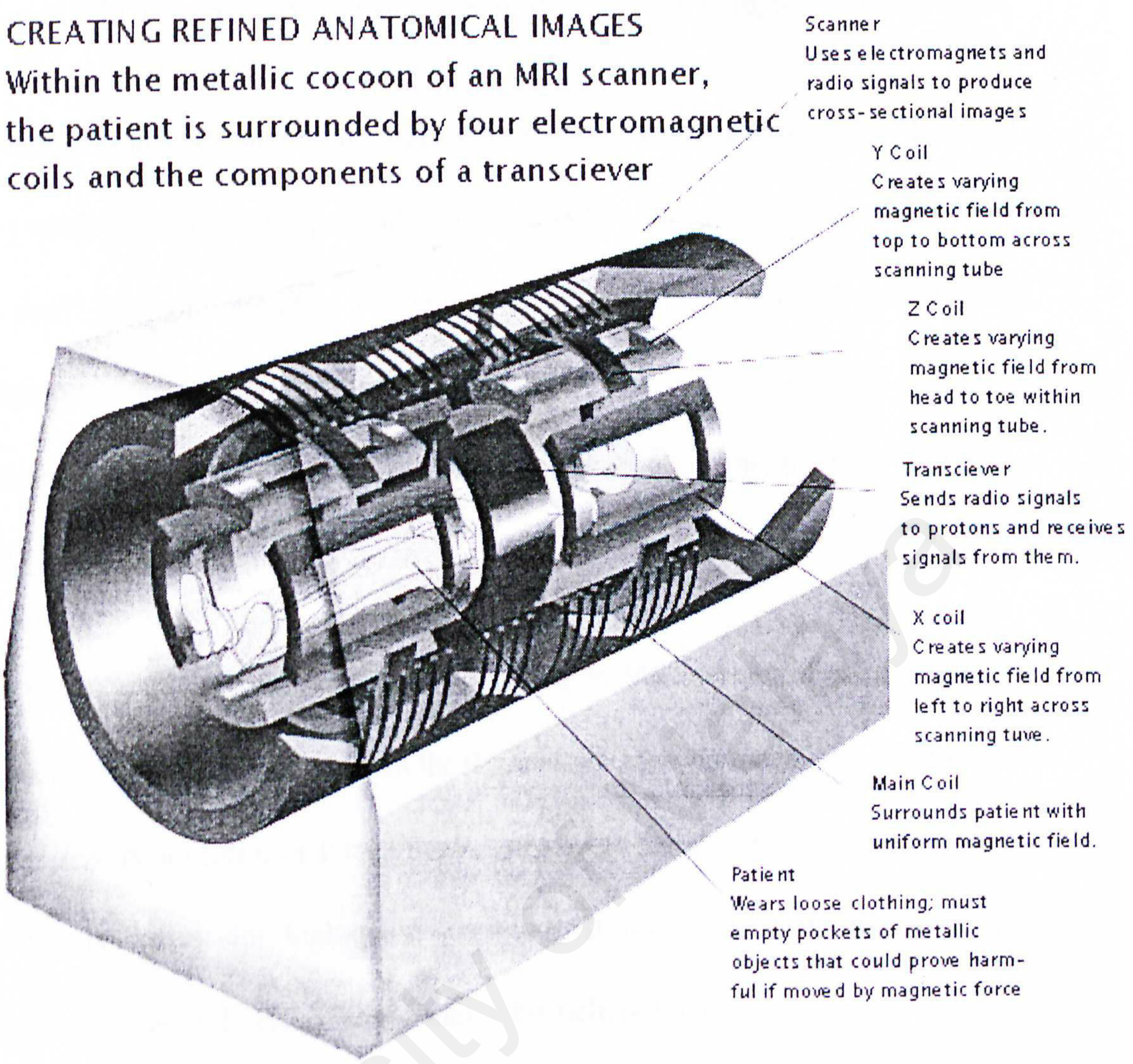


Figure 2.4 : MR scanner structure [4]

If you have ever seen an MRI machine, you know that the basic design used in most is a giant cube. The cube in a typical system might be 7 feet tall by 7 feet wide by 10 feet long (2 m by 2 m by 3 m), although new models are rapidly shrinking. There is a horizontal tube running through the magnet from front to back. This tube is known as the bore of the magnet. The patient, lying on his or her back, slides into the bore on a special table. Whether or not the patient goes in head first or feet first, as well as how far in the magnet they will go, is determined by the type of exam to be performed. MRI scanners vary in size and shape, and newer models have some degree of openness around the sides, but the basic design is the same. Once the body part to be scanned is in the exact center or isocenter of the magnetic field, the scan can begin.

In conjunction with radio wave pulses of energy, the MRI scanner can pick out a very small point inside the patient's body and ask it, essentially, "What type of tissue are you?" The point might be a cube that is half a millimeter on each side. The MRI system goes through the patient's body point by point, building up a 2-D or 3-D map of tissue types. It then integrates all of this information together to create 2-D images or 3-D models.

The biggest and most important component in an MRI system is the magnet. The magnets in use today in MRI are in the 0.5-tesla to 2.0-tesla range, or 5,000 to 20,000 gauss. A very uniform, or homogeneous, magnetic field of incredible strength and stability is critical for high-quality imaging. It forms the main magnetic field. Magnets like those described above make this field possible.

Another type of magnet found in every MRI system is called a gradient magnet. There are three gradient magnets inside the MRI machine. These magnets are very, very low strength compared to the main magnetic field; they may range in strength from 180 gauss to 270 gauss, or 18 to 27 millitesla (thousandths of a tesla).

The main magnet immerses the patient in a stable and very intense magnetic field, and the gradient magnets create a variable field. The rest of an MRI system consists of a very powerful computer system, some equipment that allows us to transmit RF (radio frequency) pulses into the patient's body while they are in the scanner, and many other secondary components [3].

2.1.6 *Advantages and Disadvantages Using MRI*

MRI is ideal for:

1. Diagnosing multiple sclerosis (MS)
2. Diagnosing tumors of the pituitary gland and brain
3. Diagnosing infections in the brain, spine or joints
4. Visualizing torn ligaments in the wrist, knee and ankle
5. Visualizing shoulder injuries
6. Diagnosing tendonitis
7. Evaluating masses in the soft tissues of the body
8. Evaluating bone tumors, cysts and bulging or herniated discs in the spine
9. Diagnosing strokes in their earliest stages

These are but a few of the many of reasons to perform an MRI scan.

The fact that MRI systems do not use ionizing radiation is a comfort to many patients, as is the fact that MRI contrast materials have a very low incidence of side effects. Another major advantage of MRI is its ability to image in any plane. CT is limited to one plane, the axial plane (in the loaf-of-bread analogy, the axial plane would be how a loaf of bread is normally sliced). An MRI system can create axial images as well as images in the sagitall plane (slicing the bread side-to-side lengthwise) and coronally (think of the layers of a layer cake) or any degree in between, without the patient ever moving. If you have ever had an X-ray, you know that every time they take a different picture, you have to move. The three gradient magnets discussed earlier allow the MRI system to choose exactly where in the body to acquire an image and how the slices are oriented.

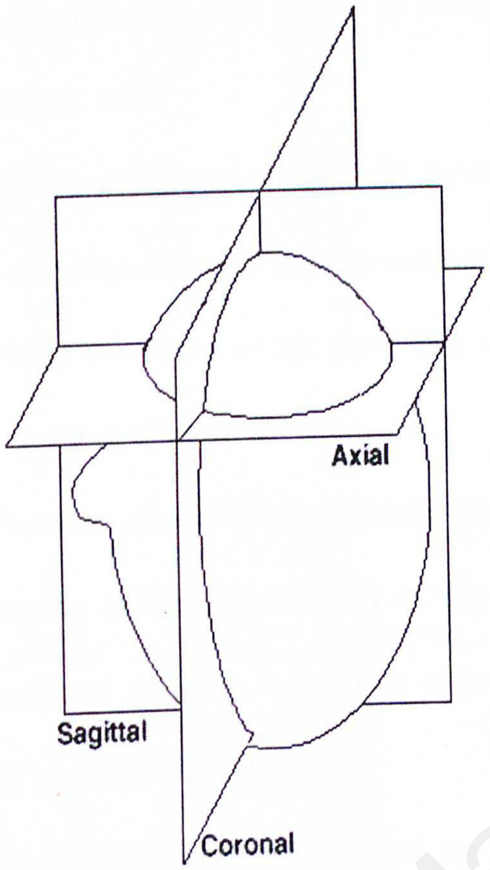


Figure2.5 : Axial, coronal and sagital slices

MRI does have drawbacks, however. For example:

1. There are many people who cannot safely be scanned with MRI (for example, because they have pacemakers), and also people who are too big to be scanned.
2. There are many claustrophobic people in the world, and being in an MRI machine can be a very disconcerting experience for them.
3. The machine makes a tremendous amount of noise during a scan. The noise sounds like a continual, rapid hammering. Patients are given earplugs or stereo headphones to muffle the noise (in most MRI centers you can even bring your own cassette or CD to listen to). The noise is due to the rising electrical current in the wires of the gradient magnets being

opposed by the main magnetic field. The stronger the main field, the louder the gradient noise.

4. MRI scans require patients to hold very still for extended periods of time. MRI exams can range in length from 20 minutes to 90 minutes or more. Even very slight movement of the part being scanned can cause very distorted images that will have to be repeated.
5. Orthopedic hardware (screws, plates, artificial joints) in the area of a scan can cause severe artifacts (distortions) on the images. The hardware causes a significant alteration in the main magnetic field. Remember, a uniform field is critical to good imaging.
6. MRI systems are very, very expensive to purchase, and therefore the exams are also very expensive.

The almost limitless benefits of MRI for most patients far outweigh the few drawbacks [3].

2.1.7 Conclusion

MRI provides an unparalleled view inside the human body. The level of detail we can see is extraordinary compared with any other imaging modality. MRI is the method of choice for the diagnosis of many types of injuries and conditions because of the incredible ability to tailor the exam to the particular medical question being asked. By changing exam parameters, the MRI system can cause tissues in the body to take on different appearances. This is very helpful to the radiologist (who reads the MRI) in determining if something seen is normal or not. We know that when we do "A," normal tissue will look like "B" -- if it doesn't, there might be an abnormality. MRI systems can also image flowing blood in virtually any part of the body. This allows us to perform studies that show the arterial system in the body, but not the tissue around it. In many cases, the MRI system can do this without a contrast injection, which is required in vascular radiology.

2.2 Study on Artificial Neural Networks (ANN)

2.2.1 Introduction to ANN

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well [5].

2.2.2 A Brief History About ANN

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

The history of neural networks that was described above can be divided into several periods:

First Attempts: There were some initial simulations using formal logic. McCulloch and Pitts (1943) developed models of neural networks based on their understanding of neurology. These models made several assumptions about how neurons worked. Their networks were based on simple neurons which were considered to be binary devices with fixed thresholds. The results of their model were simple logic functions such as "a or b" and "a and b". Another attempt was by using computer simulations. Two groups (Farley and Clark, 1954; Rochester, Holland, Haibit and Duda, 1956). The first group (IBM researchers) maintained closed contact with neuroscientists at McGill University. So whenever their models did not work, they consulted the neuroscientists. This interaction established a multidisciplinary trend which continues to the present day.

Promising & Emerging Technology: Not only was neuroscience influential in the development of neural networks, but psychologists and engineers also contributed to the progress of neural network simulations. Rosenblatt (1958) stirred considerable interest and activity in the field when he designed and developed the Perceptron. The Perceptron had three layers with the middle layer known as the association layer. This system could learn to connect or associate a given input to a random output unit.

Another system was the ADALINE (ADAptive LInear Element) which was developed in 1960 by Widrow and Hoff (of Stanford University). The ADALINE was an analogue electronic device made from simple components. The method used for learning was different to that of the Perceptron, it employed the Least-Mean-Squares (LMS) learning rule.

Period of Frustration & Disrepute: In 1969 Minsky and Papert wrote a book in which they generalized the limitations of single layer Perceptrons to multilayered systems. In the book they said: "...our intuitive judgment that the extension (to multilayer systems) is sterile". The significant result of their book was to eliminate funding for research with neural network simulations. The conclusions supported the disenchantment of researchers in the field. As a result, considerable prejudice against this field was activated.

Innovation: Although public interest and available funding were minimal, several researchers continued working to develop neuromorphically based computational methods for problems such as pattern recognition. During this period several paradigms were generated which modern work continues to enhance. Grossberg's (Steve Grossberg and Gail Carpenter in 1988) influence founded a school of thought which explores resonating algorithms. They developed the ART (Adaptive Resonance Theory) networks based on biologically plausible models. Anderson and Kohonen developed associative techniques independent of each other. Klopf (A. Henry Klopf) in 1972, developed a basis for learning in artificial neurons based on a biological principle for neuronal learning called heterostasis.

Werbos (Paul Werbos 1974) developed and used the back-propagation learning method, however several years passed before this approach was popularized. Back-propagation nets are probably the most well known and widely applied of the neural networks today. In essence, the back-propagation net. is a Perceptron with multiple layers, a different threshold function in the artificial neuron, and a more robust and capable learning rule.

Amari (A. Shun-Ichi 1967) was involved with theoretical developments: he published a paper which established a mathematical theory for a learning basis (error-correction method) dealing with adaptive pattern classification. While Fukushima (F. Kunihiko) developed a step wise trained multilayered neural network for interpretation of handwritten characters. The original network was published in 1975 and was called the Cognitron.

Re-Emergence: Progress during the late 1970s and early 1980s was important to the re-emergence on interest in the neural network field. Several factors influenced this movement. For example, comprehensive books and conferences provided a forum for people in diverse fields with specialized technical languages, and the response to conferences and publications was quite positive. The news media picked up on the increased activity and tutorials helped disseminate the technology. Academic programs appeared and courses were introduced at most major Universities (in US and Europe). Attention is now focused on funding levels throughout Europe, Japan and the US and as this funding becomes available, several new commercial with applications in industry and financial institutions are emerging.

Today: Significant progress has been made in the field of neural networks-enough to attract a great deal of attention and fund further research. Advancement beyond current commercial applications appears to be possible, and research is advancing the field on many fronts. Neurally based chips are emerging and applications to complex problems developing. Clearly, today is a period of transition for neural network technology.

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much [5].

2.2.3 Advantages Using ANN

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage [5].

2.2.4 ANN vs Conventional Computers

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency [5].

2.2.5 *How the Human Brain Learns?*

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called *dendrites*. The neuron sends out spikes of electrical activity through a long, thin stand known as an *axon*, which splits into thousands of branches. At the end of each branch, a structure called a *synapse* converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes. [5]

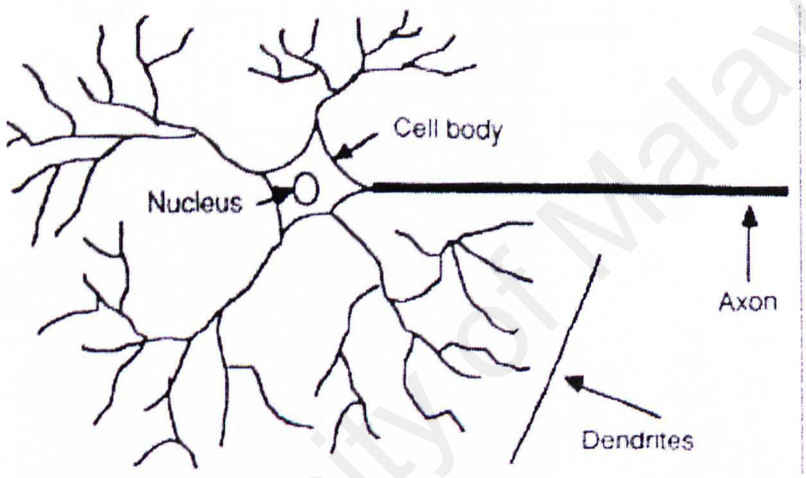


Figure 2.6 : Components of a neuron

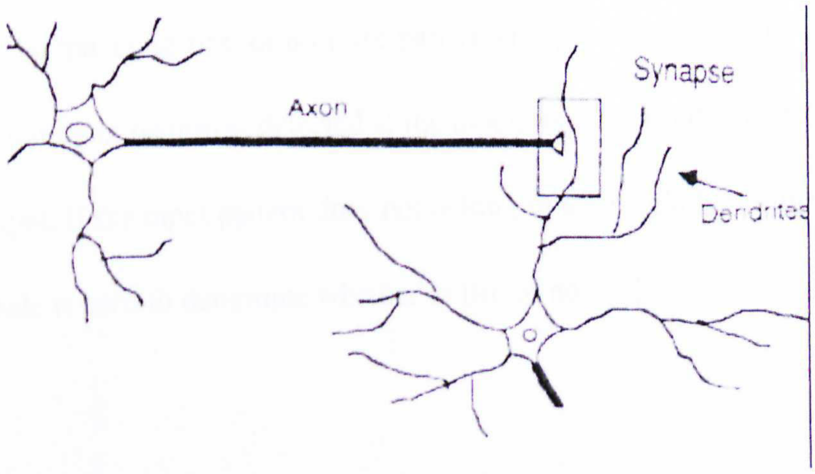


Figure 2.7 : The synapse

2.2.6 From Human Neurons to Artificial Neurons

We conduct these neural networks by first trying to deduce the essential features of neurons and their interconnections. We then typically program a computer to simulate these features. However because our knowledge of neurons is incomplete and our computing power is limited, our models are necessarily gross idealizations of real networks of neurons. [5]

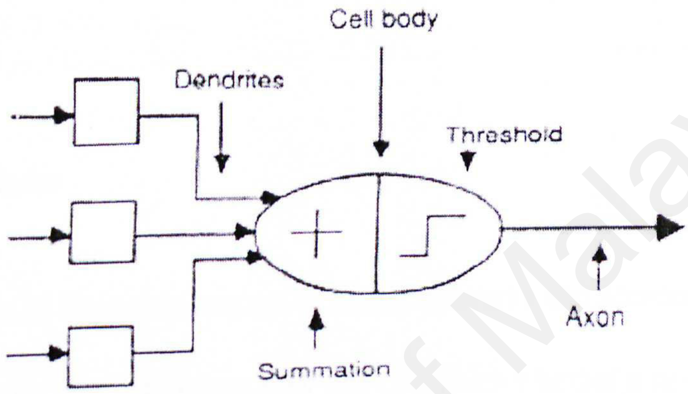


Figure 2.8 : The neuron model

2.2.7 A simple neuron

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not. [5]

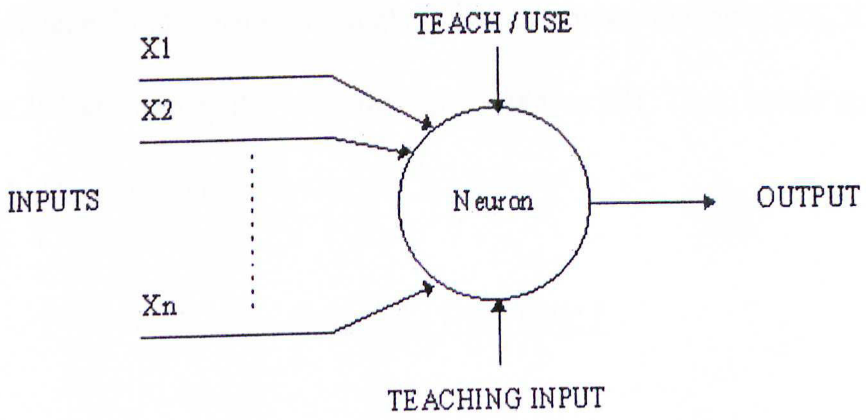


Figure 2.9 : A simple neuron

2.2.8 Firing Rules

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained.

A simple firing rule can be implemented by using Hamming distance technique. The rule goes as follows:

Take a collection of training patterns for a node, some of which cause it to fire (the 1-taught set of patterns) and others which prevent it from doing so (the 0-taught set). Then the patterns not in the collection cause the node to fire if, on comparison, they have more input elements in common with the 'nearest' pattern in the 1-taught set than with the 'nearest' pattern in the 0-taught set. If there is a tie, then the pattern remains in the undefined state.

For example, a 3-input neuron is taught to output 1 when the input (X1, X2 and X3) is 111 or 101 and to output 0 when the input is 000 or 001. Then, before applying the firing rule, the truth table is;

Table 2.1 : Truth table 1

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0/1	0/1	0/1	1	0/1	1

As an example of the way the firing rule is applied, take the pattern 010. It differs from 000 in 1 element, from 001 in 2 elements, from 101 in 3 elements and from 111 in 2 elements. Therefore, the 'nearest' pattern is 000 which belongs in the 0-taught set. Thus the firing rule requires that the neuron should not fire when the input is 001. On the other hand, 011 are equally distant from two taught patterns that have different outputs and thus the output stays undefined (0/1).

By applying the firing in every column the following truth table is obtained;

Table 2.2 : Truth table 2

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0	0/1	0/1	1	1	1

The difference between the two truth tables is called the *generalization of the neuron.* Therefore the firing rule gives the neuron a sense of similarity and enables it to respond 'sensibly' to patterns not seen during training [5].

*2.2.9 ANN Architecture : **Feed-forward networks***

Feed-forward ANNs (figure 2.10) allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down [5].

*2.2.10 ANN Architecture :**Feedback networks***

Feedback networks (figure 2.11) can have signals traveling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations [5].

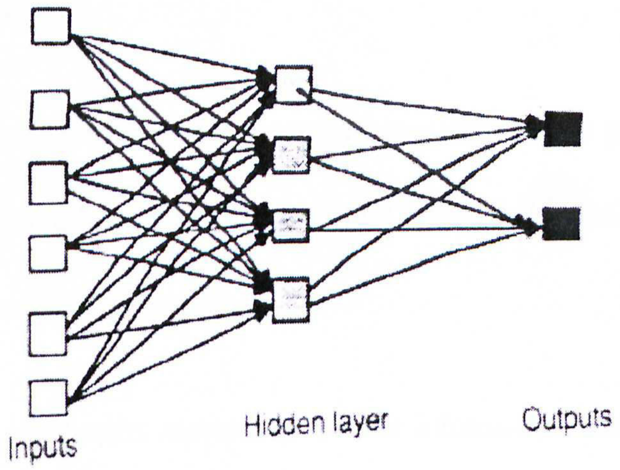


Figure 2.10 : An example of a simple feedforward network

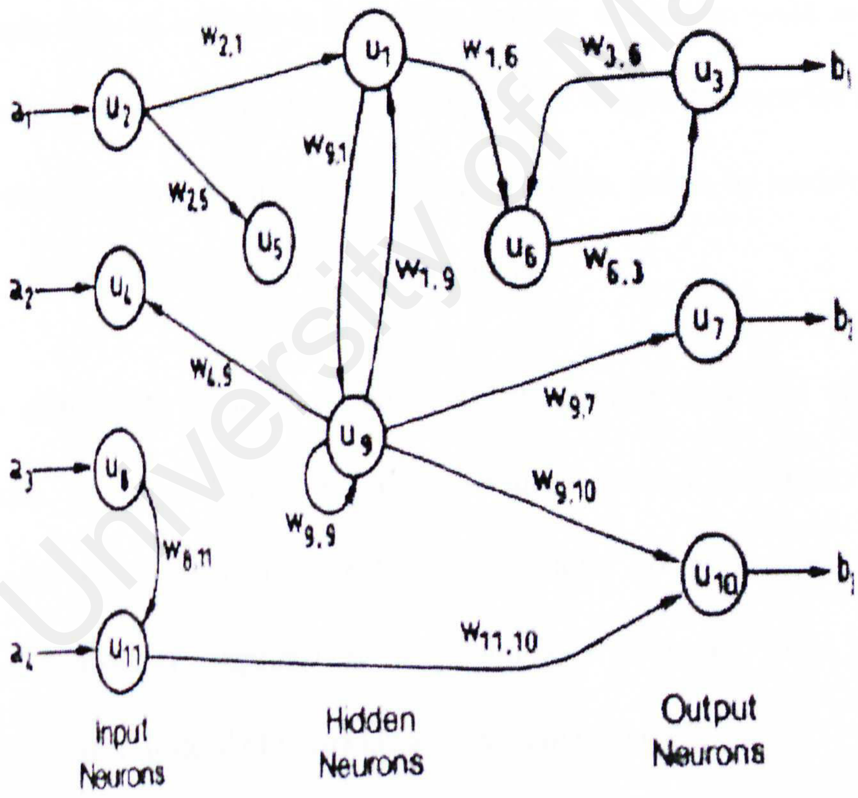


Figure 2.11 : An example of a complicated network

2.2.11 Network Layers

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units.

The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering [5].

2.2.12 Conclusion

The computing world has a lot to gain from neural networks. Their ability to learn by example makes them very flexible and powerful. Furthermore there is no need to devise an algorithm in order to perform a specific task; i.e. there is no need to understand the internal mechanisms of that task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture.

Neural networks also contribute to other areas of research such as neurology and psychology. They are regularly used to model parts of living organisms and to investigate the internal mechanisms of the brain.

Perhaps the most exciting aspect of neural networks is the possibility that some day 'consious' networks might be produced. There are a number of scientists arguing that consciousness is a 'mechanical' property and that 'conscious' neural networks are a realistic possibility.

Finally, I would like to state that even though neural networks have a huge potential we will only get the best of them when they are integrated with computing, AI, fuzzy logic and related subjects.

2.3 Study on Fuzzy Logic (FL)

2.3.1 Introduction to Fuzzy Logic

Fuzzy Logic is an innovative approach to help control non-repeating or unpredictable systems with accuracy. It uses a list of rules rather than complicated mathematical expressions. These rules are modeled after rational decisions previously made by humans in unpredictable situations. Therefore, Fuzzy Logic more closely approximates the human thought process than standard PID (Proportional/Integral/Derivative) control methods do. Since some process control systems are difficult to control with only PID, the addition of Fuzzy Logic provides an excellent solution.

2.3.2 A Brief History About Fuzzy Logic

The precision of mathematics owes its success in large part to the efforts of Aristotle and the philosophers who preceded him. In their efforts to devise a concise theory of logic, and later mathematics, the so-called "Laws of Thought" were posited [7]. One of these, the "Law of the Excluded Middle," states that every proposition must either be True or False. Even when Parminedes proposed the first version of this law (around 400 B.C.) there were strong and immediate objections: for example, Heraclitus proposed that things could be simultaneously True and not True.

It was Plato who laid the foundation for what would become fuzzy logic, indicating that there was a third region (beyond True and False) where these opposites "tumbled about." Other, more modern philosophers echoed his sentiments, notably Hegel, Marx, and Engels. But it was Lukasiewicz who first proposed a systematic alternative to the bi-valued logic of Aristotle [8].

In the early 1900's, Lukasiewicz described a three-valued logic, along with the mathematics to accompany it. The third value he proposed can best be translated as the term "possible," and he assigned it a numeric value between True and False. Eventually, he proposed an entire notation and axiomatic system from which he hoped to derive modern mathematics.

Later, he explored four-valued logics, five-valued logics, and then declared that in principle there was nothing to prevent the derivation of an infinite-valued logic. Lukasiewicz felt that three- and infinite-valued logics were the most intriguing, but he ultimately settled on a four-valued logic because it seemed to be the most easily adaptable to Aristotelian logic.

Knuth proposed a three-valued logic similar to Lukasiewicz's, from which he speculated that mathematics would become even more elegant than in traditional bi-valued logic. His insight, apparently missed by Lukasiewicz, was to use the integral range [-1, 0 +1] rather than [0, 1, 2]. Nonetheless, this alternative failed to gain acceptance, and has passed into relative obscurity.

It was not until relatively recently that the notion of an infinite-valued logic took hold. In 1965 Lotfi A. Zadeh published his seminal work "Fuzzy Sets" ([12], [13]) which described the mathematics of fuzzy set theory, and by extension fuzzy logic. This theory proposed making the membership function (or the values False and True) operate over the range of real numbers [0.0, 1.0]. New operations for the calculus of logic were proposed, and showed to be in principle at least a generalization of classic logic. It is this theory which we will now discuss.

2.3.3 *Fuzzy Set*

The Fuzzy set is a range of values. Each value has a grade of membership between 0 and 1. Logic expressions define values as either true or false. Fuzzy Logic uses labels such as "moderate", "somewhat", and "a little" to express degrees of intensity. A process can be "somewhat slow," "medium-hot," etc. This is illustrated in Figure 2.12.

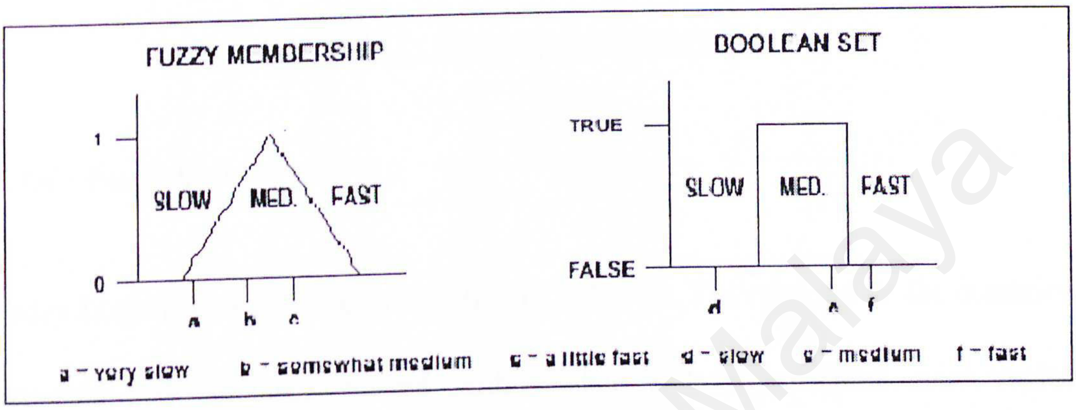
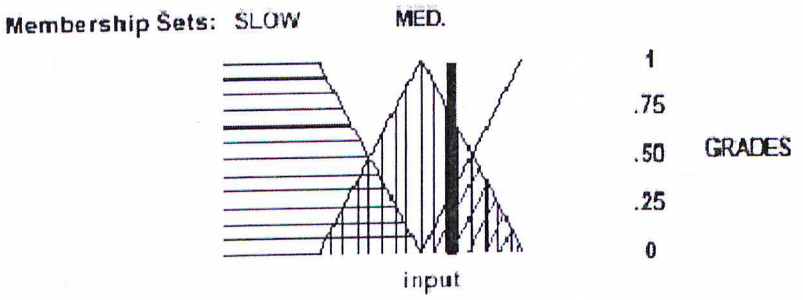


Figure 2.12 : Definition of speed in terms of Fuzzy Logic and Boolean

The figure on the left is a Fuzzy membership. The figure on the right is a Boolean set. The Fuzzy set in figure 2.12 has a triangular shape. The set can be any shape including a trapezoid or a bell curve. The triangle shape is used most often today because it is easy to work with and produces results similar to the more complex bell curve. When Fuzzy sets cover a whole range of possible values, they overlap so that a given value may be a member of more than one set. This makes a value unique. See Figure 2.13 [6].



A value indicated by the red line is a member of the sets med. and fast. It has a grade of .75 in the med. set and .25 in the fast set.

Figure 2.13 : Overlapping membership sets

2.3.4 *Fuzzy Rules*

Fuzzy Logic uses a set of rules to define its behavior. The rules define the conditions expected and outcomes desired with If/Then statements. These rules replace formulas. They must cover all situations that may occur but they don't have to be written for every possible combination.

Fuzzy Logic can understand statements such as:

- "if the temperature is close to set point"
- "if temperature change is very slow"
- "then add a little heat"

It understands because it defines terms such as "close", "very", and "a little" by using Fuzzy sets.

The rules control a system. The temperature of the system is read by a sensor. This is the temperature input. Its value is subtracted from the previous temperature input and divided by the time elapsed since the previous temperature reading.

This calculation results in the rate of temperature change and is called the rate input. See Figure 2.14.

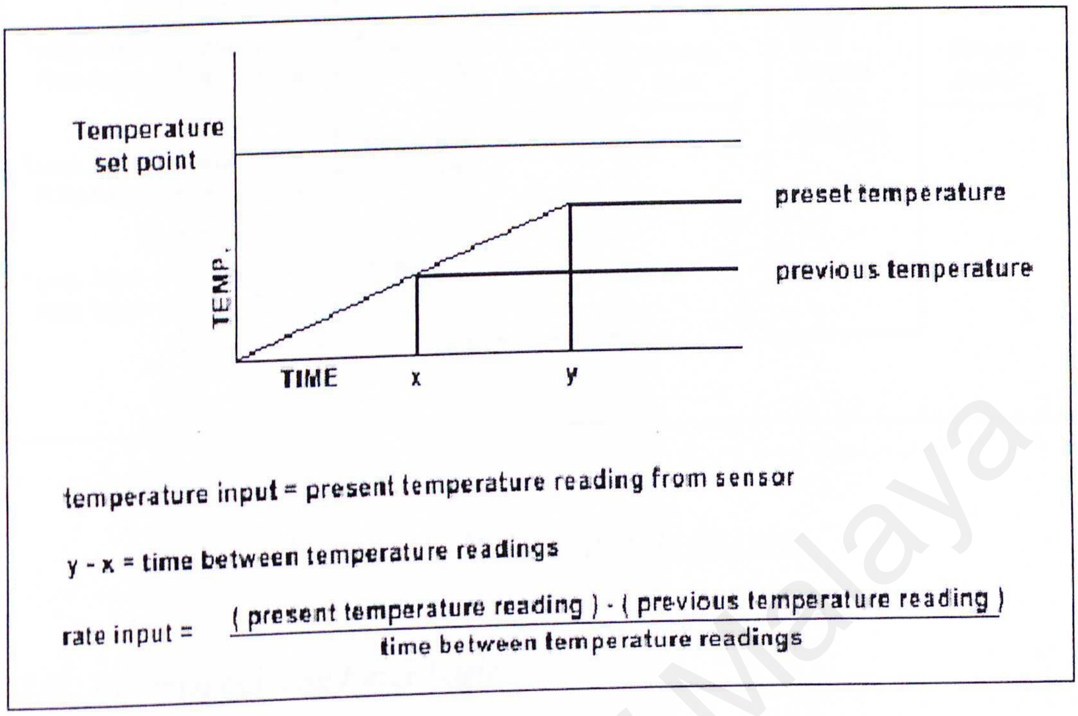


Figure 2.14 : Input of the rules

Each rule takes the temperature and rate inputs and determines its appropriate output. All of the outputs from the individual rules are combined into one term called the Logical Sum. This Logical Sum is analyzed. The result is the output of the control. The output interfaces with the output device of the system. The inputs are then read again and the cycle starts again for continuous control. See Figure 2.15 [9,10].

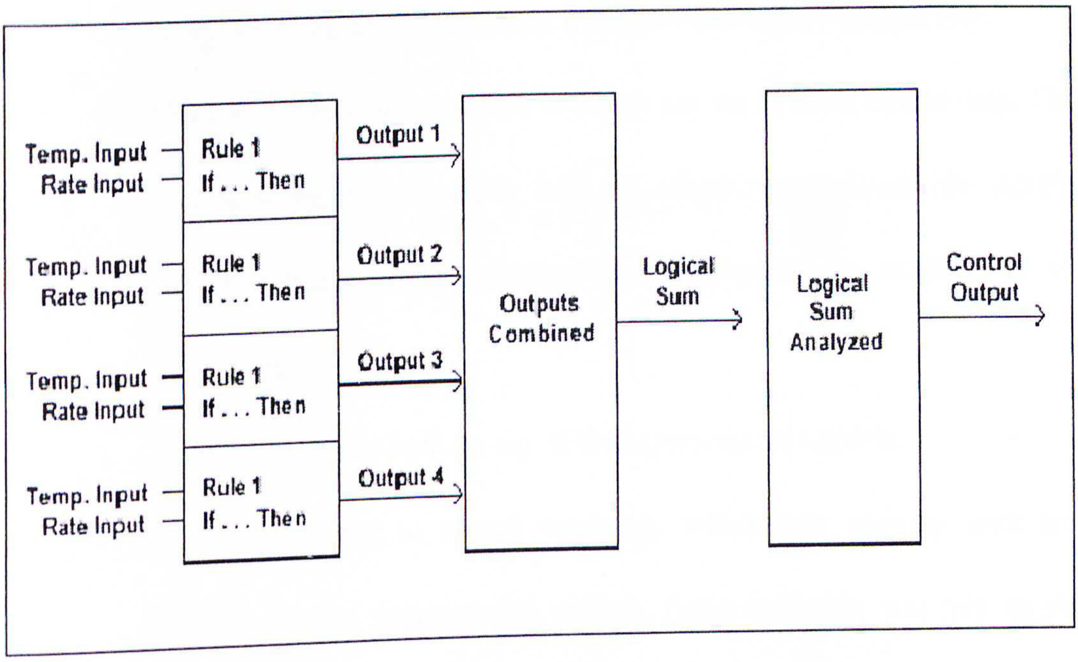


Figure 2.15 : Steps to applying the rules

2.3.5 Advantages Using Fuzzy Logic

Here is a list of general observations about fuzzy logic:

1. Fuzzy logic is conceptually easy to understand.
2. The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy nice is the "naturalness" of its approach and not its far-reaching complexity.
3. Fuzzy logic is flexible.
4. With any given system, it's easy to massage it or layer more functionality on top of it without starting again from scratch.
5. Fuzzy logic is tolerant of imprecise data.
6. Everything is imprecise if you look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

7. Fuzzy logic can model nonlinear functions of arbitrary complexity.
8. You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like ANFIS (Adaptive Neuro-Fuzzy Inference Systems), which are available in the Fuzzy Logic Toolbox.
9. Fuzzy logic can be built on top of the experience of experts.
10. In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand your system.
11. Fuzzy logic can be blended with conventional control techniques.
12. Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.
13. Fuzzy logic is based on natural language.
14. The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.

The last statement is perhaps the most important one and deserves more discussion. Natural language, that which is used by ordinary people on a daily basis, has been shaped by thousands of years of human history to be convenient and efficient. Sentences written in ordinary language represent a triumph of efficient communication. We are generally unaware of this because ordinary language is, of course, something we use every day. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, fuzzy logic is easy to use [9,10].

2.4 Study on Neuro-fuzzy System (NF)

2.4.1 Introduction to Neuro-fuzzy System

Every intelligent technique has particular computational properties example like ability to learn, explanation of decisions that make them suited for particular problems and not for others. For example, while neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions.

These limitations have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques.

Hybrid systems are also important when considering the varied nature of application domains. Many complex domains have many different component problems, each of which may require different types of processing. If there is a complex application which has two distinct sub-problems, say a signal processing task and a serial reasoning task, then a neural network and an expert system respectively can be used for solving these separate tasks.

The use of intelligent hybrid systems is growing rapidly with successful applications in many areas including process control, engineering design, financial trading, credit evaluation, medical diagnosis, and cognitive simulation.

Neural networks are used to *tune* membership functions of fuzzy systems that are employed as decision-making systems for controlling equipment. Although fuzzy logic can encode expert knowledge directly using rules with linguistic labels, it usually takes a lot of time to design and tune the membership functions which quantitatively define these linguistic labels.

Neural network learning techniques can automate this process and substantially reduce development time and cost while improving performance. In theory, neural networks, and fuzzy systems are equivalent in that they are convertible, yet in practice each has its own advantages and disadvantages. For neural networks, the knowledge is automatically acquired by the backpropagation algorithm, but the learning process is relatively slow and analysis of the trained network is difficult (black box). Neither is it possible to extract structural knowledge (rules) from the trained neural network, nor can we integrate special information about the problem into the neural network in order to simplify the learning procedure.

Fuzzy systems are more favorable in that their behavior can be explained based on fuzzy rules and thus their performance can be adjusted by tuning the rules. But since, in general, knowledge acquisition is difficult and also the universe of discourse of each input variable needs to be divided into several intervals, applications of fuzzy systems are restricted to the fields where expert knowledge is available and the number of input variables is small. To overcome the problem of knowledge acquisition, neural networks are extended to automatically extract fuzzy rules from numerical data. Cooperative approaches use neural networks to optimize certain parameters of an ordinary fuzzy system, or to preprocess data and extract fuzzy (control) rules from data.

The various neuro fuzzy unification scheme developed till date can possibly be classified into three major group :

1. Neural Fuzzy System
2. Fuzzy Neural System
3. Co-operative System

Neural fuzzy systems are fuzzy systems implemented by neural networks. Fuzzy neural systems are neural networks, capable of handling fuzzy information. The inputs, outputs and weights of fuzzy neural networks could be fuzzy sets, often fuzzy numbers or membership value. The Co-operative systems are those which use different paradigms (neuro or fuzzy) to solve various facets of the same problem. All these three paradigms taken together is known as neuro-fuzzy computing.

2.5 Study on MR Image Segmentation

2.5.1 *Introduction to MR Image Segmentation*

Image segmentation is a technique fro partitioning the image into meaningful subregions or objects with the same attributes, and usually is heavily dependent upon the image and application.

A number of algorithm based upon the approached such as histogram analysis, region growing, edge detection, and pixel classification have been proposed. In general, these method make use of the local information (i.e. the gray-level values of the neighbouring pixels) and global information (i.e. the overall gray-level distribution of the image) fro image segmentation.

In the histogram analysis, one or more thresholds of gray levels have to be determined to separating the objects from the background. Thus this is usually referred to as the threshold method.

For the global thresholding method, a single value of gray level is estimated on the basis of the gray-level distribution of the whole image. In contrast, a local thresholding method is one that devide a given image into subregions and determines a grey-level threshold in each threshold in each subregion. The method proposed by Ostu is an example of the global thresholding technique, in which an optimal threshold may be determined by minimizing the criterion functions derived from the within class, between class and total variance.

Region growing is a technique that starts at a selected pixel as the seed and extent to all of the neighbouring pixels that are homogeneous in gray level , color, and texture to form the closed regions of interest.

Edge detection-based image segmentation detects local discontinuities as edges and then connects those edges to enclose the object. A pixel classification approach is one that classifies the pixel into associated regions based upon their gray levels or spatial relationship.

Neural network approach have also been extensively investigated in edge detection and image segmentation. A comparison of a supervised multilayer feedforward neural network, a dynamic multilayer perceptron trained with cascade correlation, and Fuzzy C-mean unsupervised clustering as methods of segmenting MR brain image into seven classes was investigated by Hall *et al.*

An edge detection algorithm based on the Hopfield Neural Network was proposed by Chao and Dhawan. Tan *et al.* presented and edge detection approach based upon objective minimization using simulated annealing.

The segmentation of MR images by the use of a probabilistic neural network was proposed by Morrison *et al.*, and the segmentation of MR brain image by mean field simulated annealing was discussed by Snyder *et al.* Dhawan and Arata presented a self-organizing feature map algorithm fro the segmentation of medical images by competitive learning.

A fuzzy clustering strategy for segmentation has been extensively studied by many investigators. For example, Brandt *et al.* used the fuzzy c-means approach to estimate the volume of cerebrospinal fluid (CSF), white and gray matters from transaxial MRI brain image.

Here are several examples of system has been developed for volume segmentation and 3D modelling of human anatomy through my review.

2.5.1. *Example 1 : Slice-by-slice segmentation (2-D)*[11]

Segmentation steps are as follows ;

Step 1 : Select a sagittal, coronal or axial slice.

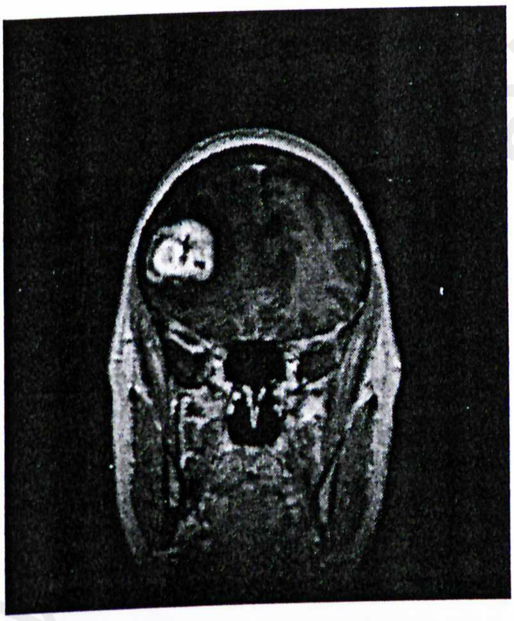


Figure 2.17 : Slice #29, coronal was selected.

Step 2 : Select a seed point inside tumor

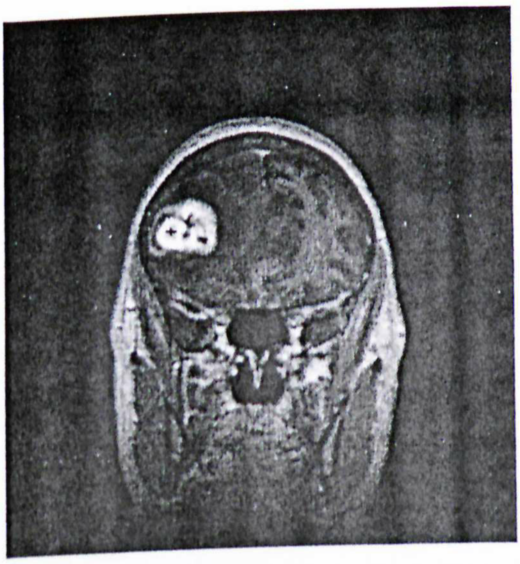


Figure 2.18 : Seed point was selected.

Step 3. Result of automatic segmentation.

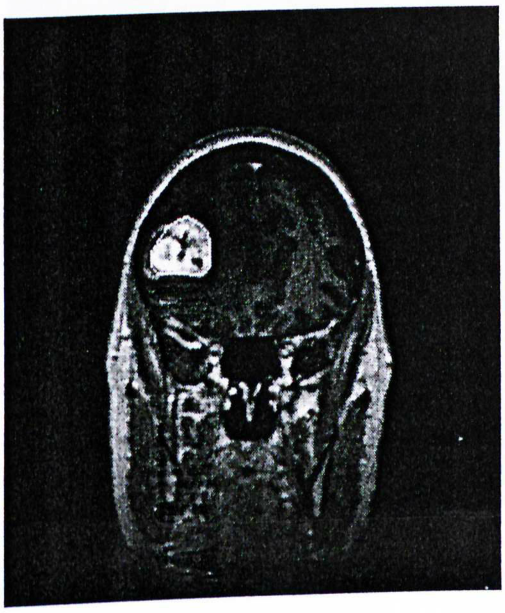


Figure 2.19 : Automatically determined tumor boundary

Step 4 : Manual modification.

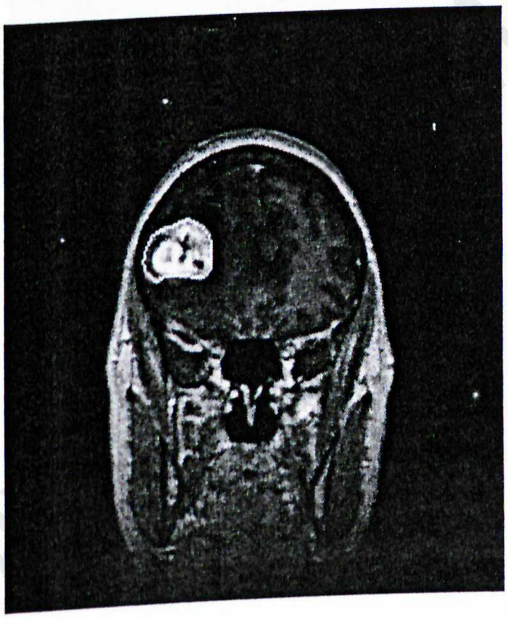


Figure 2.20 : Manually modified boundary

Step 5 : Now user can select slices preceding or following the initial slice for segmentation.

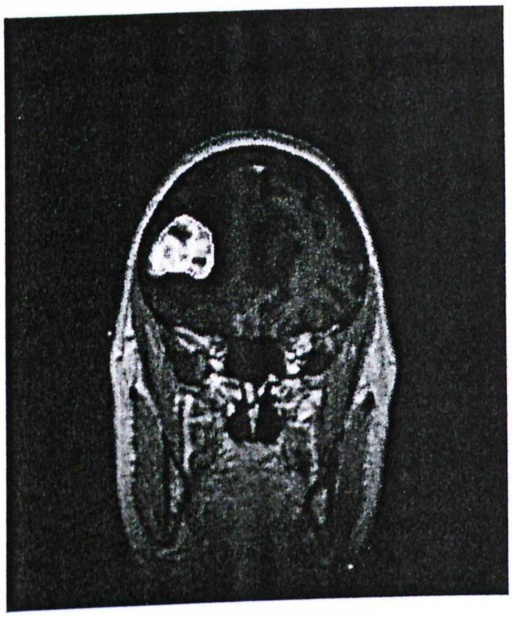


Figure 2.21 : Automatic segmentation of slice #30.

Figure 2.22 : Automatic segmentation of slice #31.

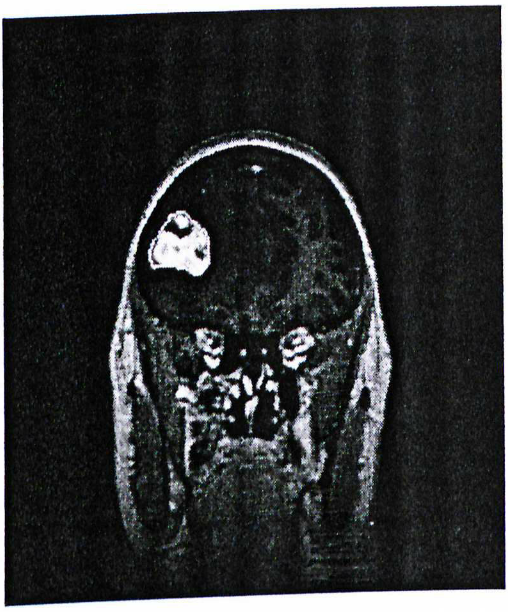


Figure 2.23 : Automatic segmentation of slice #32.

Figure 2.24 : Automatic segmentation of slice #33.

Step 6 : Process may be interrupted to revise each slice manually, if necessary.

Step 7 : Three-dimensional rendering results after segmentation of 33 slices.

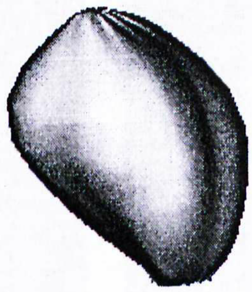


Figure 2.25 : Side view of the tumor after segmentation

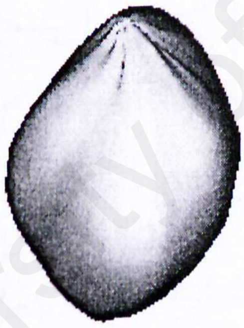


Figure 2.26 : Top view of the tumor after segmentation

2.5.2. *3D Segmentation Using a Seed Point* [11]

Segmentation steps are as follows :

Step 1: Selection of a seed point

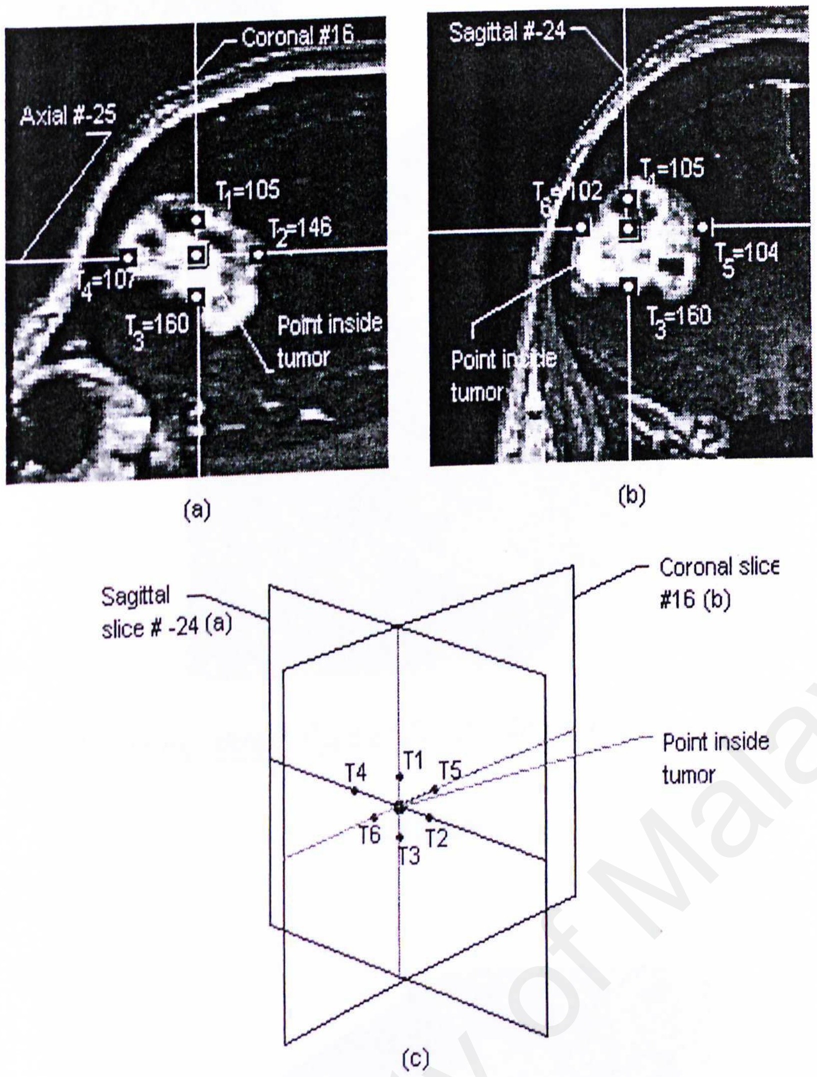


Figure 2.27 : (a) Sagittal slice #-24. (b) Coronal slice #16. (c) The cross-section of slices from figures (a) and (b), containing the seed point and six locally-maximum gradient points.

From a seed point selected by the user, the algorithm will search for six points on the boundary of the tumor. The average intensity of these points will provide the initial threshold value.

Step 2: Intensity thresholding

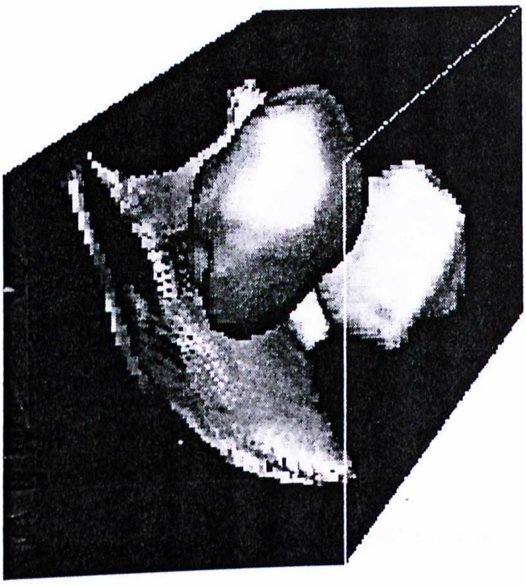


Figure 2.28 : Image thresholded at T=120 obtained from the process shown in figure 2.27

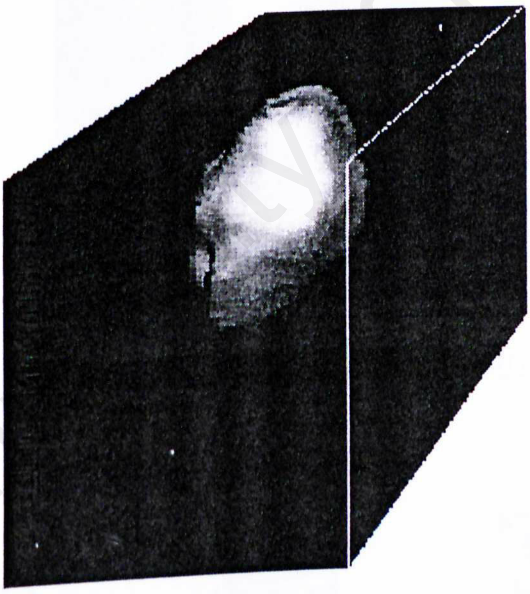


Figure 2.29 : Result of removing unnecessary surfaces from figure 2.28 that did not contain the seed point.

The volume is thresholded at the obtained threshold value T and removing regions that did not contain the seed point.

Step 3: Double thresholding

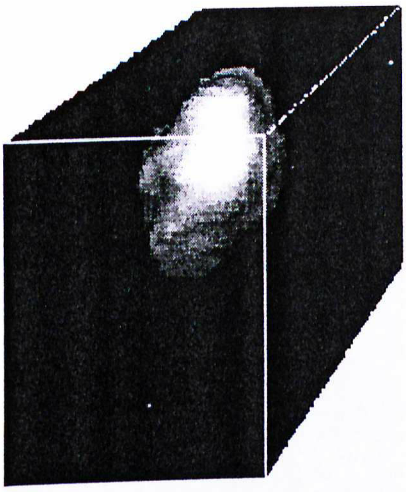


Figure 2.30 : Image thresholded at T1=99 with unnecessary regions removed.

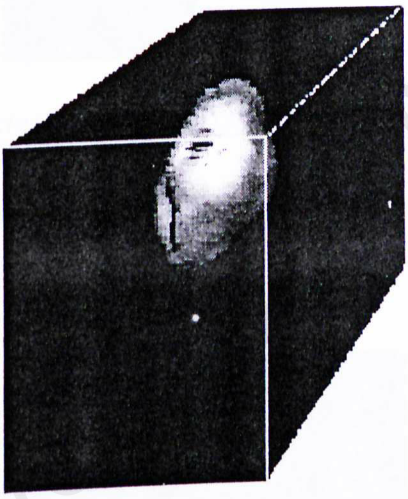


Figure 2.31 : Image thresholded at T2=148 with unnecessary regions removed.

Figure 2.32 : Different cross-sections from combining images from figures 2.29 and 2.28. The white area defines the mask that is used to filter out irrelevant edges.

By displacing the initial boundary obtained from step 2 by a distance d, two threshold values T1 and T2 are obtained. The result of thresholding the volume at T1 and T2 can be combined as shown in Fig. 2.31 to define a mask and filter out irrelevant edges.

Step 4: Edge filtering

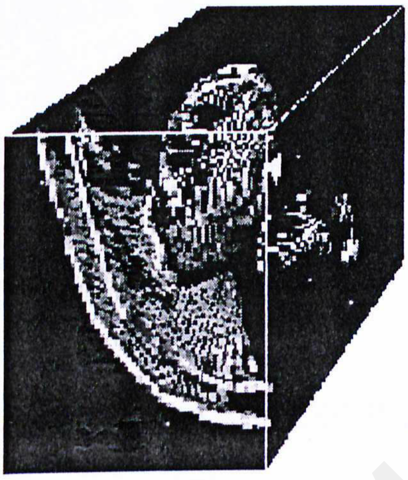


Figure 2.33 : Zero-crossing edges after removing 90% of the smallest magnitude edges.

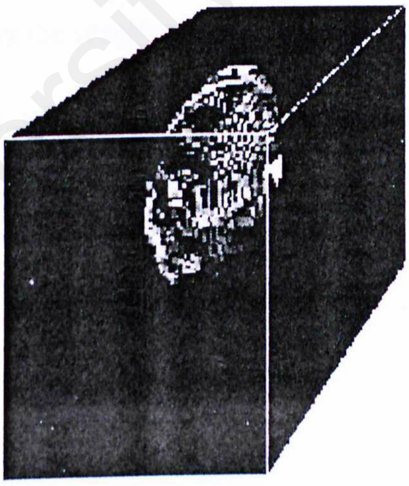


Figure 2.34 : Image edges falling inside the mask provided by step 3.

Zero-crossing edges are computed from the volumetric image. Only edges falling in the top 10% of the gradient histogram are considered. Figure 2.34 shows only the tumor-relevant edges falling inside the mask provided by double thresholding. A search for tumor boundary edges depicted in Figure 2.34 will be conducted next.

Step 5: Edge searching

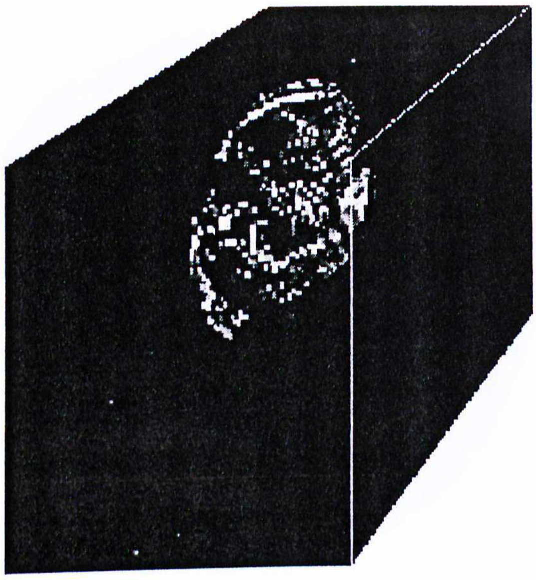


Figure 2.35: Edge points resulting from the nearest-neighbor search in the edge image of Figure 2.34.

For every point on the boundary from Figure 2.28, an edge will be assigned from Figure 2.34. By the nearest-neighbor approach, the closest edge point will be selected. Figure 2.35 shows the resulting edges after the search. In order to provide a closed tumor surface, an elastic surface is fitted to the edge points.

Step 6: Surface fitting

Figure 2.36 : Three-dimensional view of the elastic Gaussian surface (sigma=3.0) fitting to the edge points.

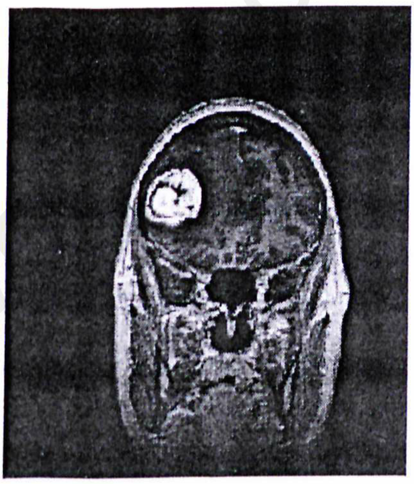


Figure 2.37 : Coronal cross-section of the segmentation result.

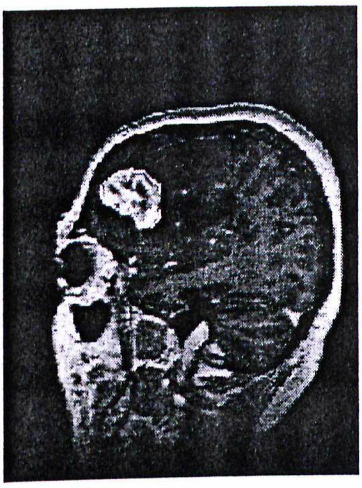


Figure 2.38 : Sagittal cross-section of the segmentation result.

Figures 2.37 and 2.38 show two slices of the segmentation result after fitting a RaG surface to the edge points (Figure 2.36).

CHAPTER THREE

PROJECT METHODOLOGY

This chapter explain about the methodology used in this system development. Figure 3.1 below shows the steps involved in the segmentation and 3D model construction from the transverse MR images for a specific anatomy of interest

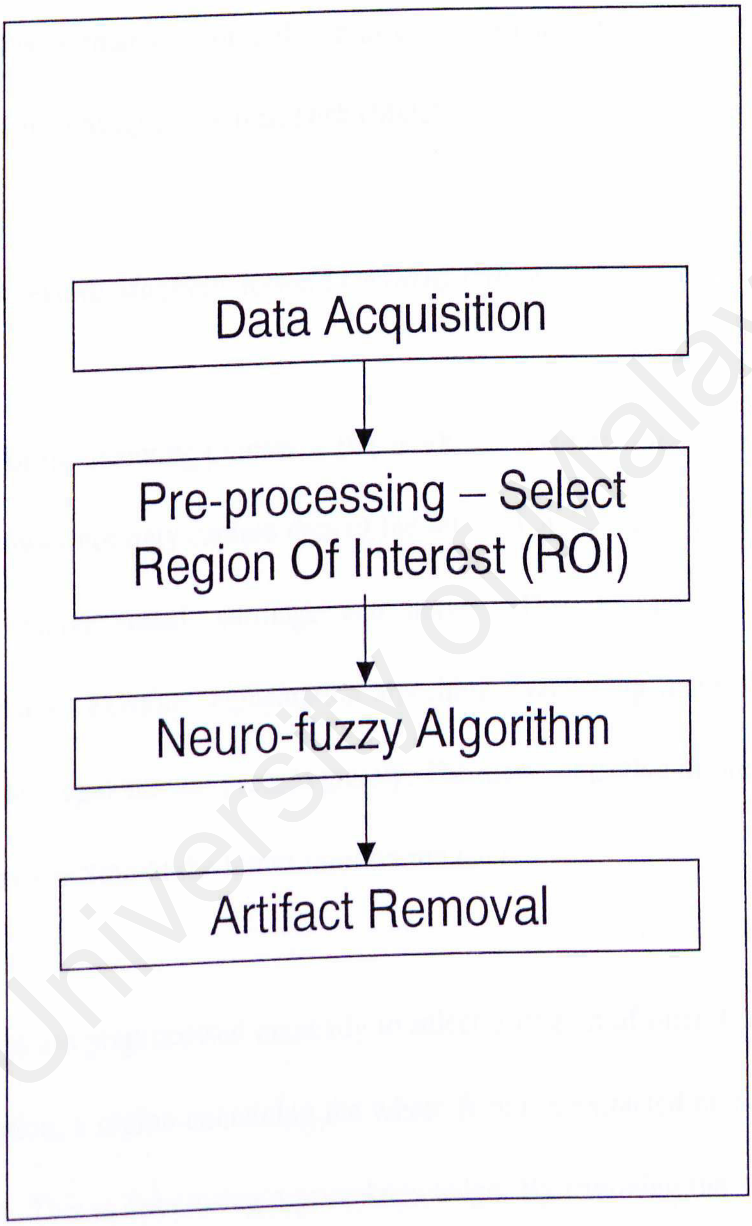


Figure3.1: Project Methodology Overview

3.1 *Data Acquisition*

The MR image data set is provided by laboratory of Artificial Neural Network, FCSIT University Malaya. The data sets are in slice of 2D image of T1 weighted transverse image of healthy normal growth and non-diseased patients. The data set acquired are stored in a 5.25 inch Magneto Optical Disk (MOD).

3.2 *Pre-processing Magnetic Resonance (MR) Images*

The main aim of the scanning process in this work is to capture a femur bone. However the MR image does not only capture data of the femur, but also together tissues like fat, skin, muscle, blood vessel, cartilage and nerves. This amount of data literally overwhelming most existing segmentation algorithm. Narrowing down the amount of data will help the segmentation process greatly. The major objective of pre-processing is to improve the extraction of the femur information later.

The MR images are preprocessed manually to select a Region of Interest (ROI). During the ROI operation, a region containing the whole femur is extracted manually from the original image. This is done using a prior knowledge. By trimming the size of images, misclassification can be reduced . The ROI steps also removed the unwanted region that could contribute artifact in the classified result. Computer processing required are also subsequently lower.

The size of the ROI must be large enough to cover the femur whole region in the MR data set. The minimum ROI size is selected and applied to the whole data set.

Consistent ROI size help to align the slices to construct the 3D model of the femur. The ROI selected for the experiment varies from data set to data set. The size of the ROI is varied so as to contain the entire data set of the femur.

3.3 Neuro-fuzzy Algorithm

This system propose a neuro-fuzzy segmentation method for transverse MR femur image using Fuzzy Hopfield Neural Network (FHNN) algorithm. Afterwards the algorithm are presented.

3.3.1 Fuzzy Hopfield Neural network (FHNN)

In this system, a novel neural network called the Fuzzy Hopfield Neural Network (FHNN) is proposed for medical image segmentation. The problem of the image segmentation is again considered as pixel classification for the minimization of the objective function. This objective function is defined as the total square of the Euclidean distance between the gray level and their class centroids. A sample does not necessarily belong to only one class. Instead, a certain degree of class membership is associated with each sample. Thus an original Hopfield Network is modified and the fuzzy C-mean clustering strategy is added.

For an image containing n gray level and c class of objects known in advance, FHNN would then consists of n x c nodes as a two dimensional array. Consequently, as with Hopfield Neural Network (HNN), the number of nodes is also independent of the image size.

The medical image segmentation problem can then be mapped onto a Hopfield Neural Network with the objective function as the energy function. This is based upon the concept that the degree of association is expected to be high among members within the same class and low among members of different classes. In other words, the total squares of the within class distance should be as small as possible. Therefore, the proposed method is to assign gray level to their associated classes such that the total squares of the Euclidean distances between samples and their class centres are minimized.

3.3.2 Fuzzy C-Mean (FCM) Algorithm

The FCM clustering method is an unsupervised classification method since it does not required any hand labeled data. FCM groups pixels by iteratively calculating a set of C cluster centers and optimizing objective function until a stopping criteria has been reached. Once clustering is completed, each image pixel belong to each class with a fuzzy membership value between 0 and 1. The fuzzy membership value represented the fact that one pixel many partially belong to more than one class. When a membership value of a pixel is one within a particular class, it is believed that the pixel contains only that particular class. The class with the maximum membership value is chosen as the class label for a given pixel.

Fuzzy membership value are interesting in MR segmentation since a slice through leg tissues represents a projection of the slice thickness onto a two-dimensional plane, contributing greatly to the partial volume effect.

Another attributes of FCM is that it tends to cluster. Therefore, in order to obtain good segmentation (or clusters of primarily one tissue type), each clustering step should required that the number of classes be larger than the actual number of distinct tissue types.

3.4 Development Tool

This section describe a few development tools used to develop this system.

3.4.1 MATLAB

MATLAB is an integrated technical computing environment that combine numeric computation, advanced graphics and visualization, and high level programming language.

3.4.2 Image Processing Toolbox

The image processing toolbox is a collection that extent the capability of the MATLAB numeric computing. The toolbox support a wide range of image processing operations including ;

1. Geometric operation
2. Neighborhood and block operation
3. Linear filtering and filter design
4. Transforms
5. Image analysis and enhancement
6. Binary image operations
7. Region of interest operation.

Many of the toolbox functions are MATLAB M-files, which contain MATLAB code that implements specialized image processing algorithm. The tool listed below all include functions that extend the Image Processing toolbox's capabilities.

1. Fuzzy Logic toolbox

   Tool to help master fuzzy logic techniques and their application to practical control problems.

2. Mapping toolbox

Tool for analyzing and displaying geographically based information from thin MATLAB.

3. Neural Network toolbox

   Comprehensive environment for neural network research, design and simulation within MATLAB.

4. Optimizing toolbox

   Tool for general and large-scale optimization of nonlinear problems, as well as for linear programming, nonlinear least squares, and time-series data modelling.

5. Signal Processing toolbox

   Tool for algorithm development, signal and linear system analysis, and time-series data modelling.

6. Statistic toolbox

   Tool for analyzing historical data, modelling system, developing statistical algorithms, and learning and teaching statistics.

7. Wavelet toolbox

   Tool for signal and image analysis compression and de-noising.

CHAPTER FOUR

SYSTEM DESIGN

This chapter is about system design. Section 4.1 introduced about the system flow and section 4.2 introduced about the interface design for the system.

4.1 System Flow

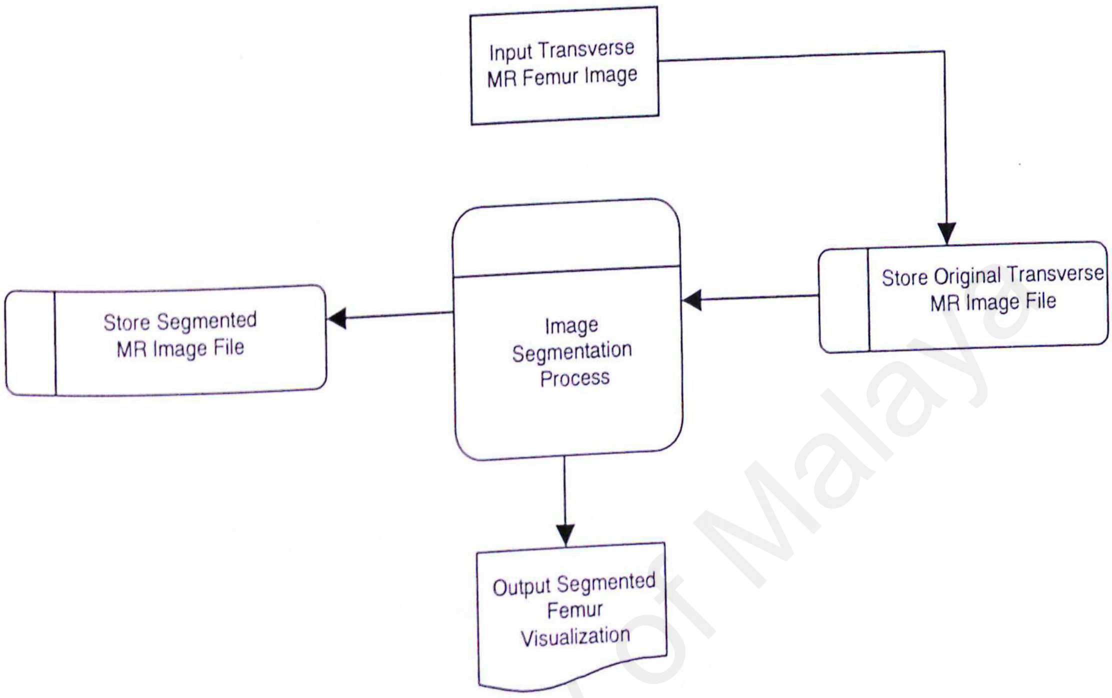


Figure 4.1 : System Flow Overview

Figure 4.1 above show a system flow. It start from input transverse MR femur image acquired from out source and stored in memory. The first process is segmenting a femur from MR image. The image for segmentation process will acquired from the memory. The output for this process is segmented femur. This image will displayed on the screen and also can store in memory.

4.2 *Interface Design*

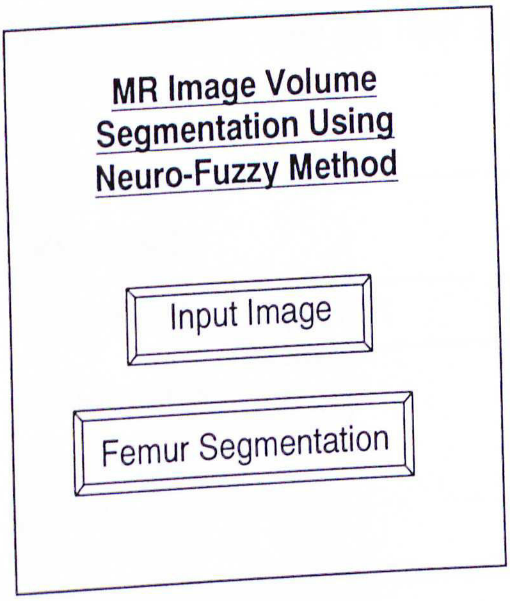


Figure 4.2 : Main Frame Interface

Figure 4.2 show the main frame interface for MR Image Volume Segmentation Using Neuro-Fuzzy Method system. This entry frame will allow the user to select either one from three main functions of this system. Button "Input Image" to input image. Button "Femur Segmentation" for segmentation process.

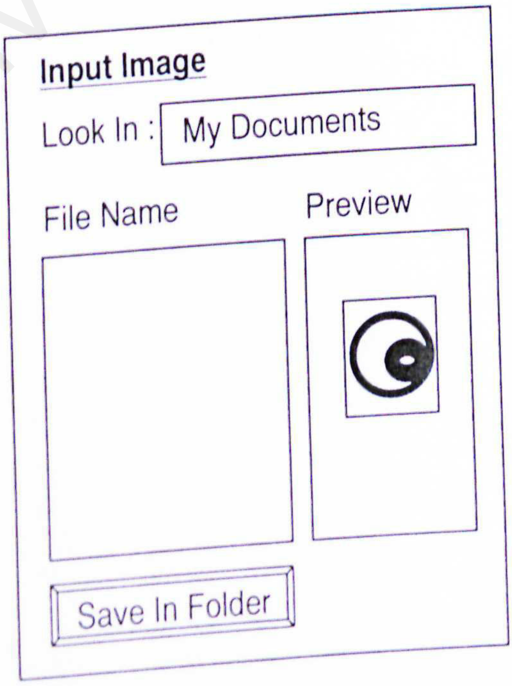


Figure 4.3 : Input Image Interface

Figure 4.3 show an input image interface. User can input MR image file from any source.

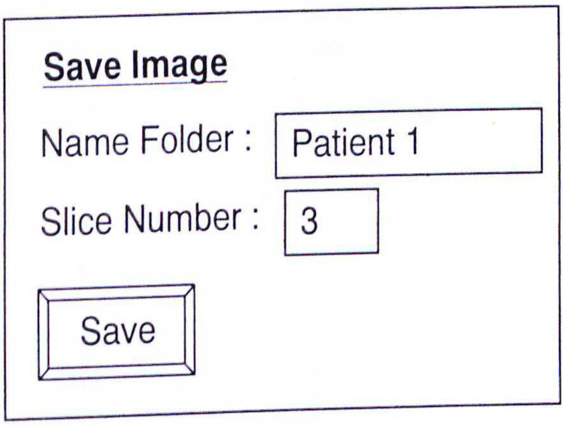


Figure 4.4 : Save Image Interface

Figure 4.4 show the design interface to save the MR Image. The user must first create a folder example "Patient1" . Then put the number of the slice. The image will be saved in slice number.

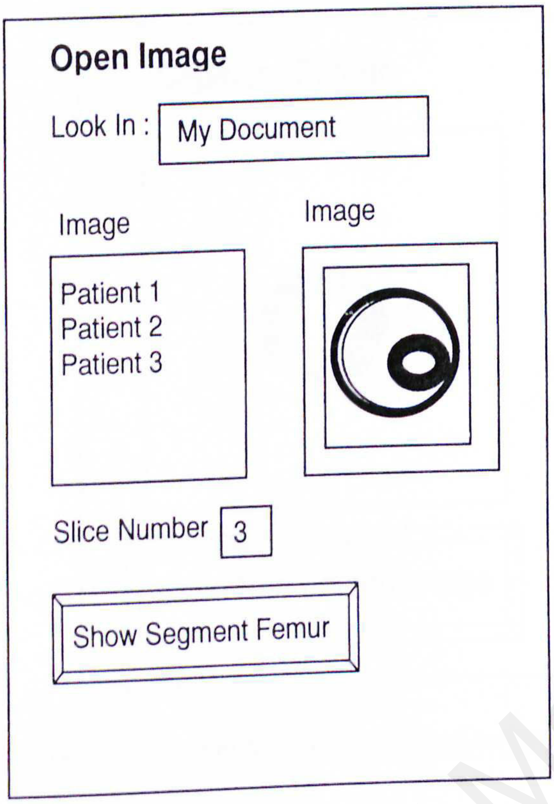


Figure 4.5 : Open File for Femur Segmentation Interface

Figure 4.5 show an interface to open an image file before segmentation process. The user must select the folder and the slice number. Then click the "Show Segment Femur" button to start the segmentation process. The segmented femur image is shown in figure 4.6 below.

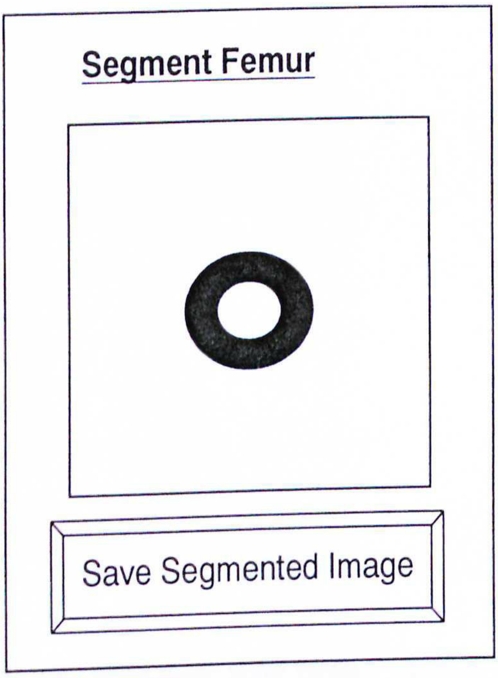


Figure 4.6 : Segmented Femur Visualization Interface

CHAPTER FIVE

SYSTEM IMPLEMENTATION

5.1 *Introduction*

Implementation is a process of translating the detailed project design into code. This whole project from requirement analysis to system testing is done individually not in a group of software development.

MatLab version 6.5 running on Windows operating system is the tool used in developing this neuro-fuzzy system. Why Matlab? It is because MatLab provide a neural network and fuzzy logic toolbox that has many built-in functions like *newhop* and *fcm*. Function *newhop* is used to create a Hopfield Network. Function *fcm* is used to do a fuzzy c means process. MatLab also provide good guidance using a help toolbox.

5.2 *System Development*

This intelligent system consists of 2 major components. First is clustering process using fuzzy technique and second is classification process using neural network technique. Below are explanations about these 2 processes.

5.2.1 *Clustering Process*

Clustering is a process to group a pixel with the same properties in one class. A coding below shows a clustering process for this neuro-fuzzy system.

```
% Step A1 : transfer original image to matrix

clear all

close all

load matrix2.m
```

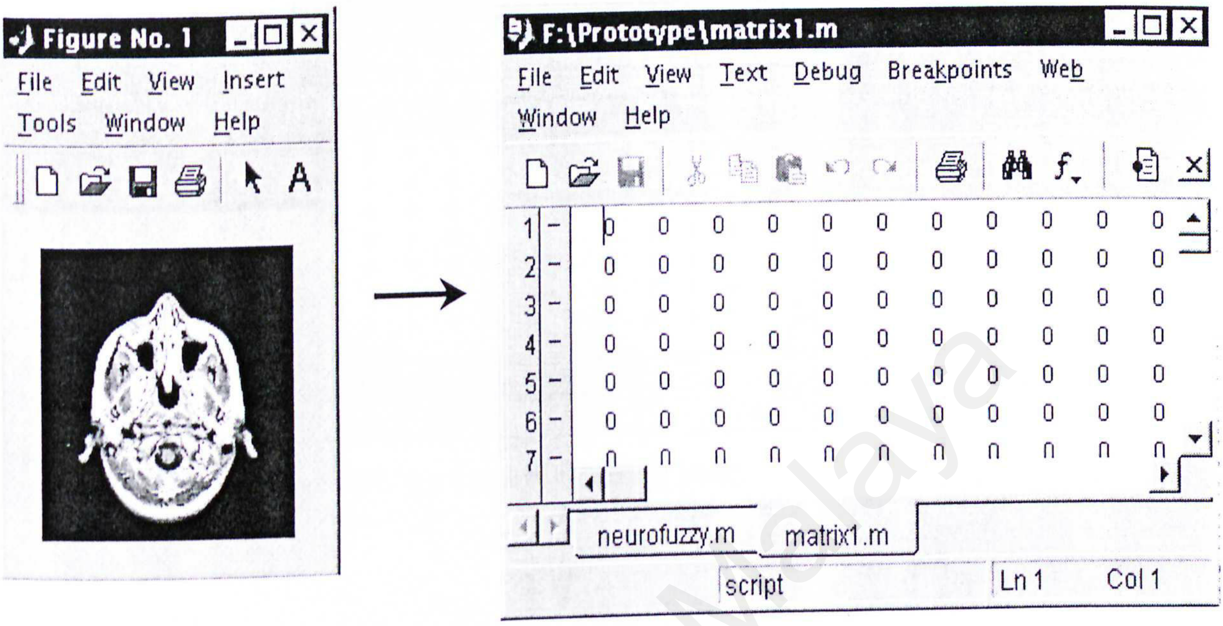
```
data = matrix2;

% Step A2 : clustering process using fuzzy c means algorithm

m = 0;

for i = 1 : 128

        for g = 1 : 128

                m = m + 1;

                w = data(i,g);

                b(m,1) = w;

        end

end

[center,u,obj_fcn] = fcm(b,4);

maxU = max(u);

% Find the data points with highest grade of membership in cluster 1

index1 = find(u(1,:) == maxU);

index2 = find(u(2,:) == maxU);

index3 = find(u(3,:) == maxU);

index4 = find(u(4,:) == maxU);

% Step A3 : transfer clustered matrix to an image

c = 0;

for a = 1 : 128

        for e = 1 : 128

                c = c + 1;
```

```
            d(a,e) = u(1,c);
            f(a,e) = u(2,c);
            o(a,e) = u(3,c);
            p(a,e) = u(4,c);
        end
end
figure, imshow(d)
figure, imshow(f)
figure, imshow(o)
figure, imshow(p)
```

Step A1 : Transfer original image to matrix

MR Image is build from 3 or 4 dimensional matrix. Each point presents a pixel value. Example the image with a pixel value 64 bits. If the value close to 64, it's look brighter or white. Otherwise if the value is close to 1, the pixel looks darker or black. So, the first step in implementation is to transfer the MR image to a matrix in size of n x n that contains a pixel value at each pixel.

A flow diagram below shows an input-output process for step A1.



IN : Original Image

OUT : n x n matrix of original image

Figure 5.1 : Input-output process for step A1

Step A2 : Clustering process using Fuzzy C Means algorithm.

The second step is clustering each pixel to a number of clusters (n) using Fuzzy C Means (fcm) algorithm. In this system, I choose n=4, meaning 4 clusters. In the fcm methods, each pixel belongs to all clusters with different degrees of membership functions. Thus the clusters are generated by partition in accordance with the membership function matrix. The fuzzy clustering approach similar to the conventional clustering approach is used to minimize the objective function in the least square errors sense.

A flow diagram below shows an input-output process for step A2.

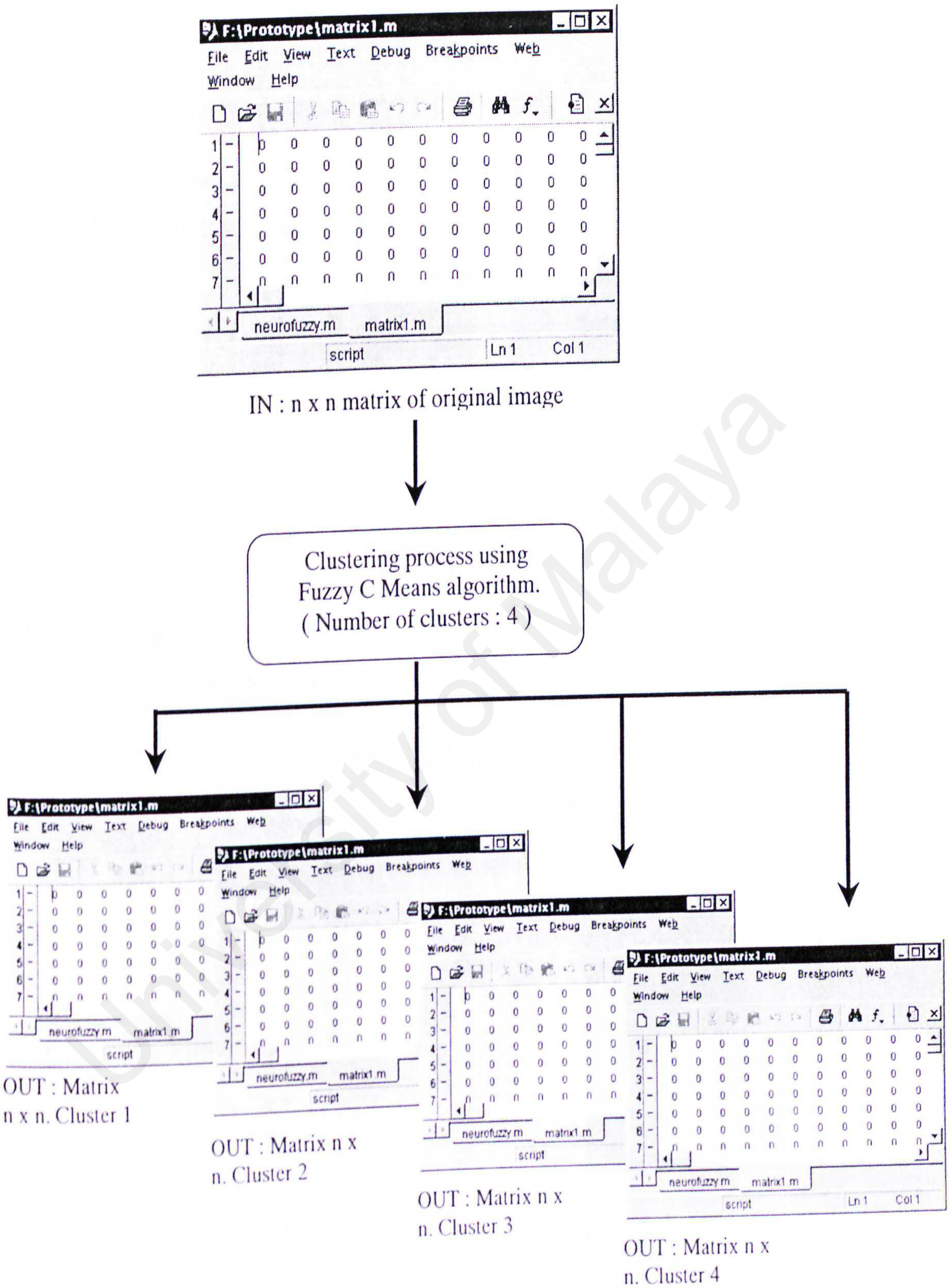


Figure 5.2 : Input-output process for step A2

Step A3 : Transfer each clustered matrix to an image

The third step is to change back a matrix n x n that present a degree for each cluster to an image.

A flow diagram below shows an input-output process for step A3.

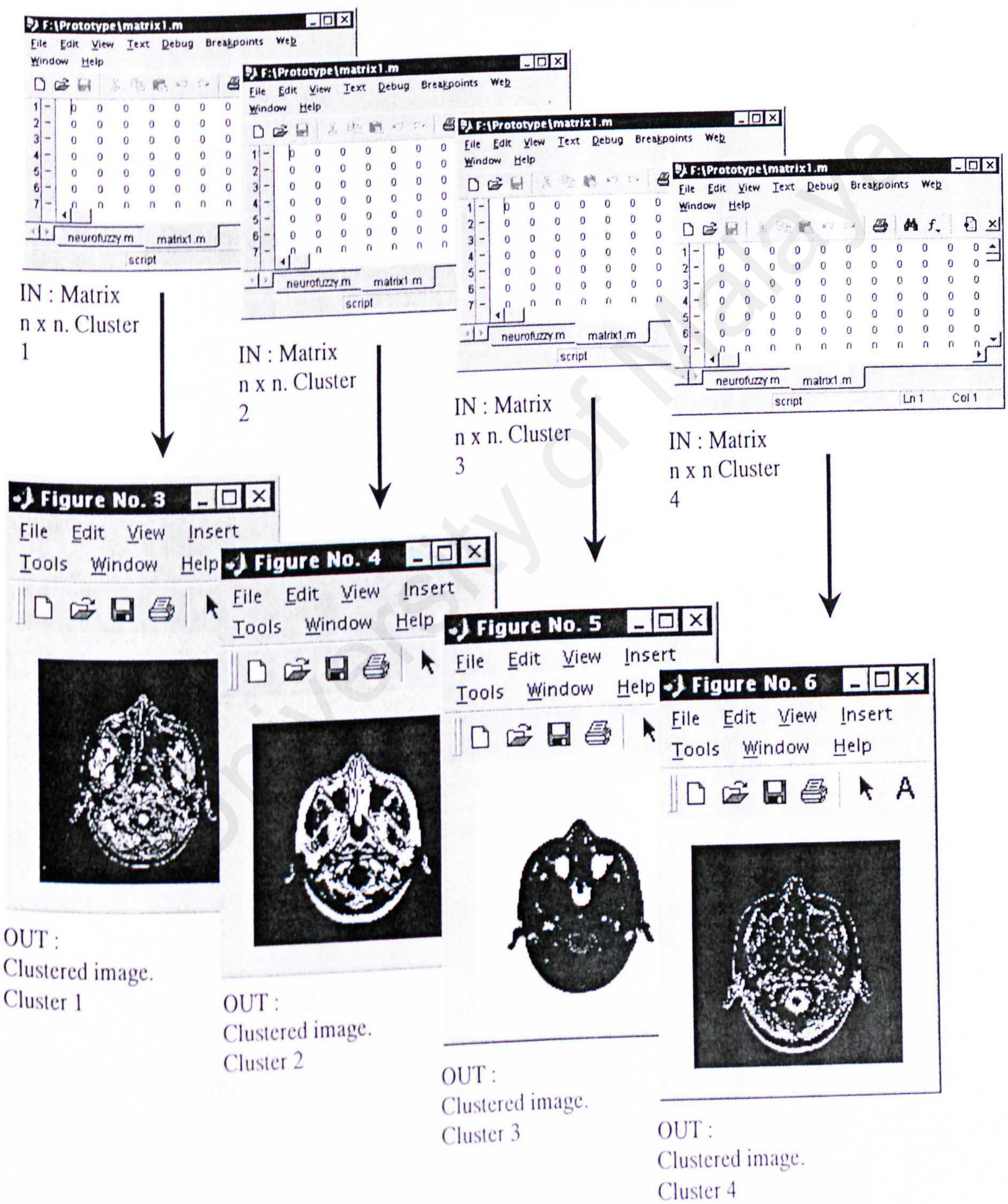


Figure 5.3 : Input-output process for step A3

5.2.2 *Classification Process*

Classification is a second component in system development. A coding below shows a classification process in this neuro-fuzzy system.

```
%Step B1 : classification process using hopfield neural network

T = [+1 -1];

net = newhop(T);

[Y,Pf,Af] = sim(net,2,[],T);

for K = 1 : 4

    if  K == 1

        P = -1 + (2*d)

    else if K == 2

        P = -1 + (2*f)

        else if K == 3

            P = -1 + (2*o)

            else

                P = -1 + (2*p)

            end

        end

    end
```

```
for G = 1:256
    for I = 1:256
        A = {P(G,I)};
        [Y,Pf,Af] = sim(net,{1 5},{},A);
        record=[cell2mat(A) cell2mat(Y)]
        R(G,I) = [record(:,6)];
    end
end
%Step B2 : transfer each classified matrix to an image
figure, imshow(R)
end
```

Step B1: Classification process using Hopfield Neural Network algorithm

The second part in this system development is to classify each pixel to the appropriate class. To do this, a neural network technique with a Hopfield Network algorithm is applied. This process classified the pixel to class 1 or –1.

The important function at this step is *newhop*. This function is used to create a Hopfield recurrent network. Hopfield networks consist of a single layer with the *dotprod* weight function, *netsum* net input function, and the *satlins* transfer function. The layer has a recurrent weight from itself and a bias.

The input for the network is taken from a matrix of clustered image. A user can specify the number of iteration or epochs in the network to get a different quality output. If the epoch value is small, the output quality is low.

Hopfield networks are designed to have stable layer outputs as defined by user- supplied targets. The algorithm minimizes the number of unwanted stable points.

A flow diagram below shows an input-output process for step B1.

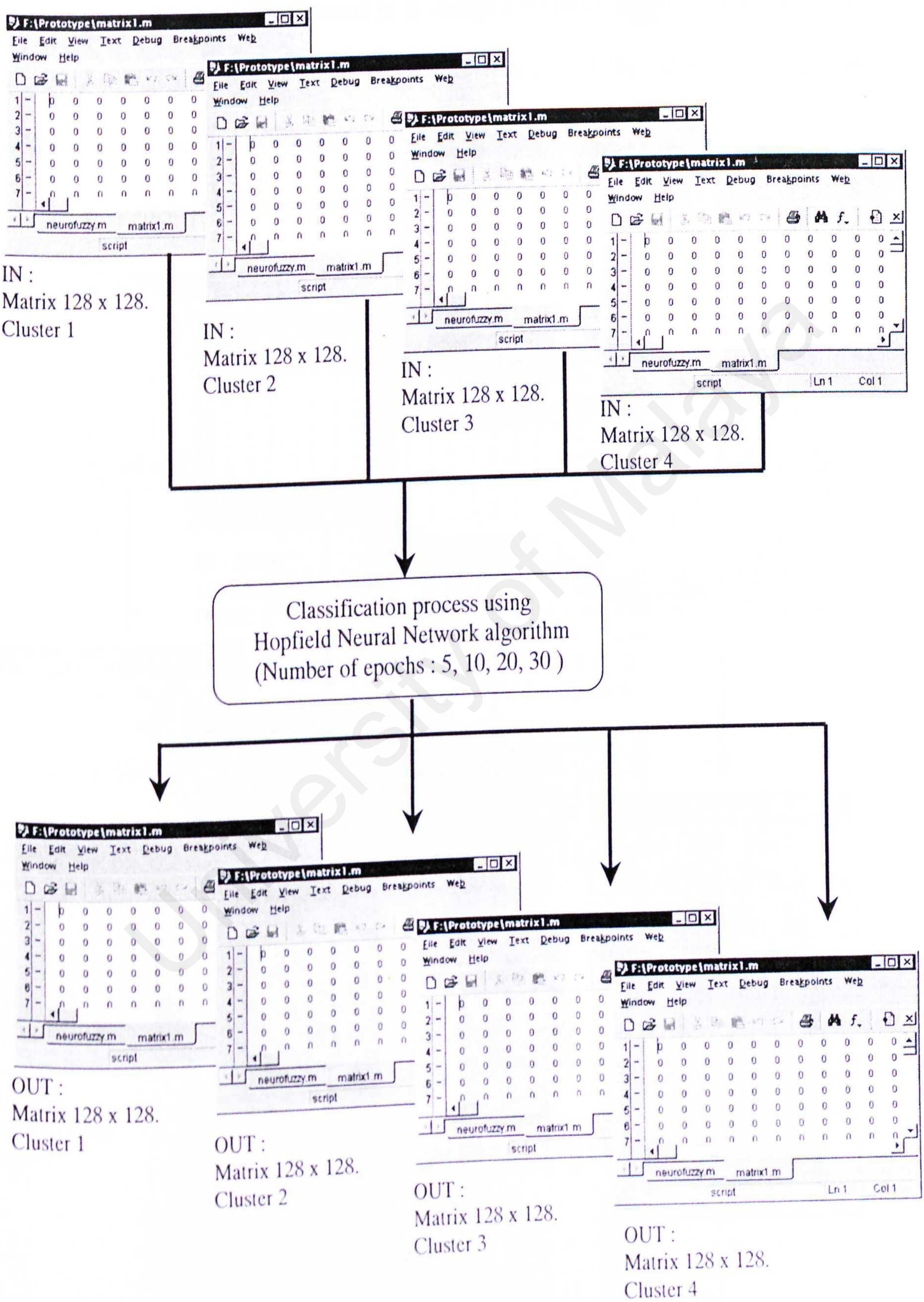


Figure 5.4 : Iinput-output process for step B1

Step B2 : Transfer each classified matrix to an image

The final step in system development in to change a classified matrix to an image. If the pixel value is 1 the color is white. If the pixel value is –1 the color is black. So the output is a black and white image.

A flow diagram below shows an input-output process for step B2.

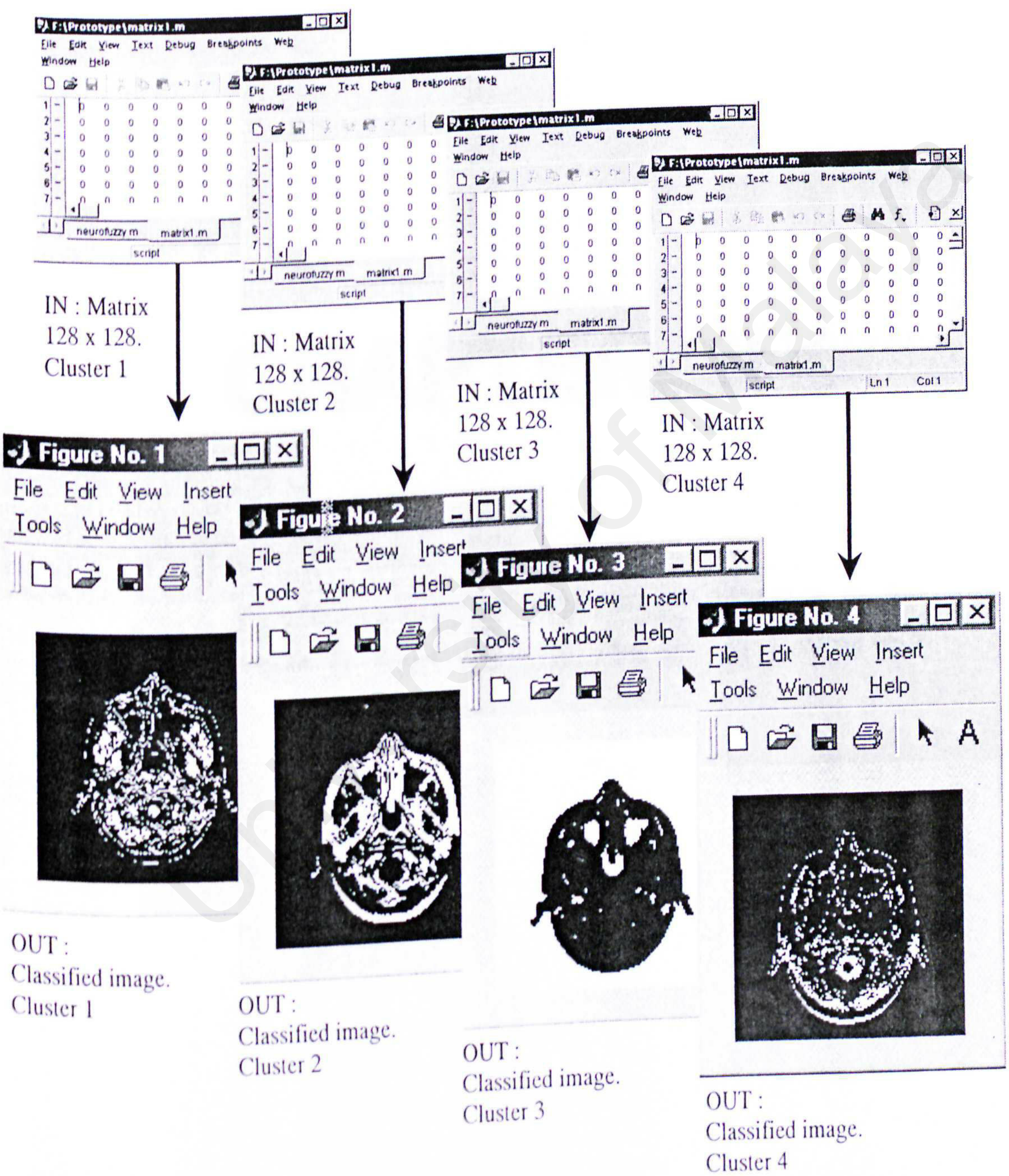


Figure 5.5 : Input-output process for step B2

CHAPTER SIX

SYSTEM TESTING

6.1 *Introduction*

Testing is the final step in system development life cycle. It is very important to evaluate the effectiveness and efficiency when we operate the whole system. However the testing operation for this system is not as conventional procedures. The main purpose is to evaluate the output quality when we change several testing parameter.

6.2 *Testing Objectives*

The objectives for a system testing are:

1. To evaluate subjectively the quality of image after neuro-fuzzy segmentation process with a different number of cluster at clustering process.
2. To evaluate subjectively the quality of image after neuro-fuzzy segmentation process with a different number of epoch at classification process.

6.3 *Testing procedures*

A flow diagram below shows a testing procedure for the first objective

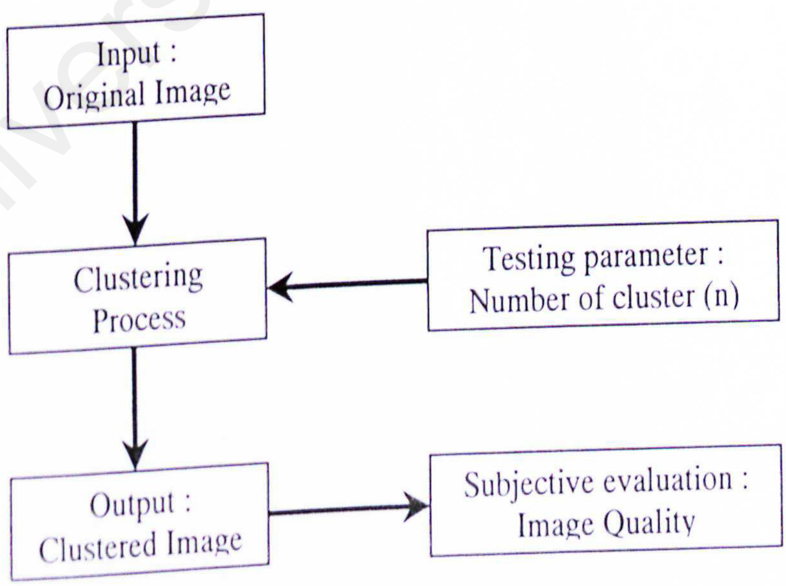


Figure 6.1 : A testing procedures for first objective

From a diagram above, a testing parameter is the number of cluster (n). Here I choose n = 2, 3, 4, 5, 6. With a different number of clusters, the output image quality is also different between each test. Refer to the result afterwards.

A flow diagram below shows a testing procedure for the second objective

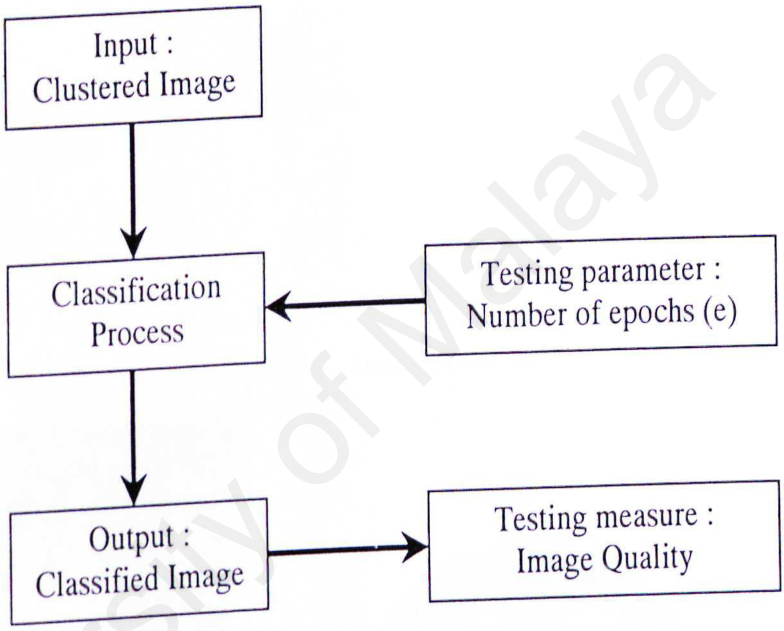


Figure 6.2 : A testing procedures for second objective

From a diagram above, a testing parameter is the number of epoch or iteration (e). Here I choose e = 5, 10, 20, 30. With a different number of epochs, the output image quality is different. Refer to the result afterwards.

6.4 *Test result*

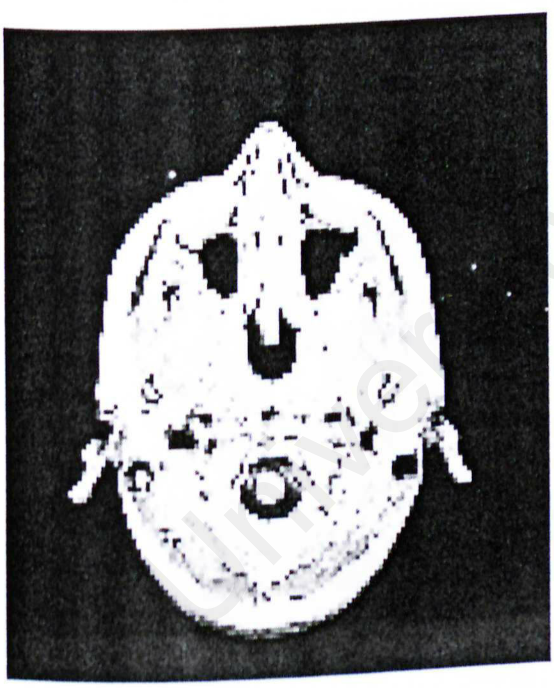
6.4.1 *System testing with a different number of cluster*

Test 1

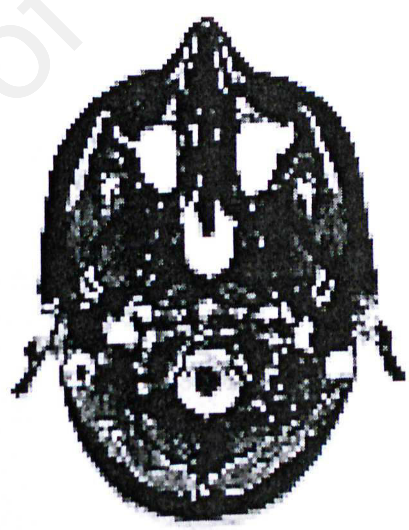
Image title : Brain MR image

Image size : 128 x 128 bits

No. cluster : 2



Title : Cluster 1



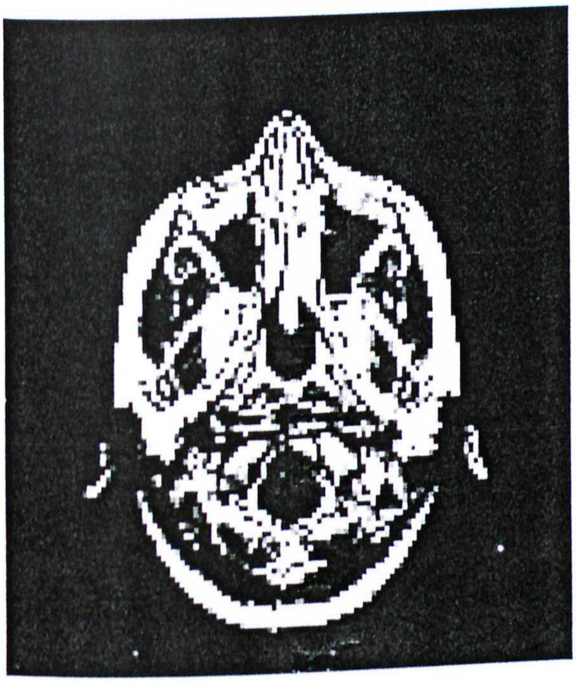
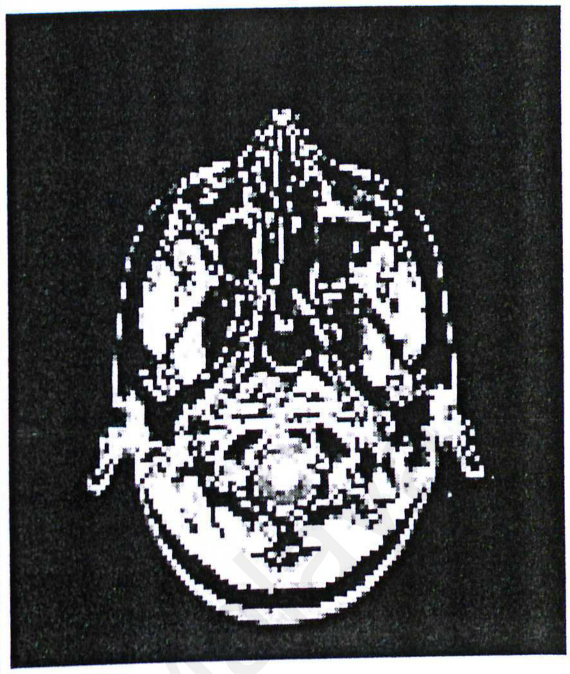
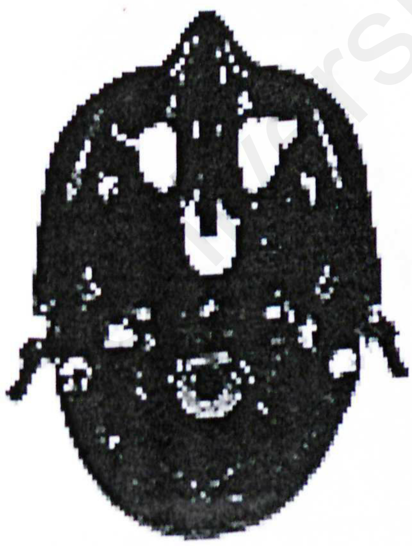
Title : Cluster 2

Test 2

Image title : Brain MR image

Image size : 128 x 128 bits

No. cluster : 3

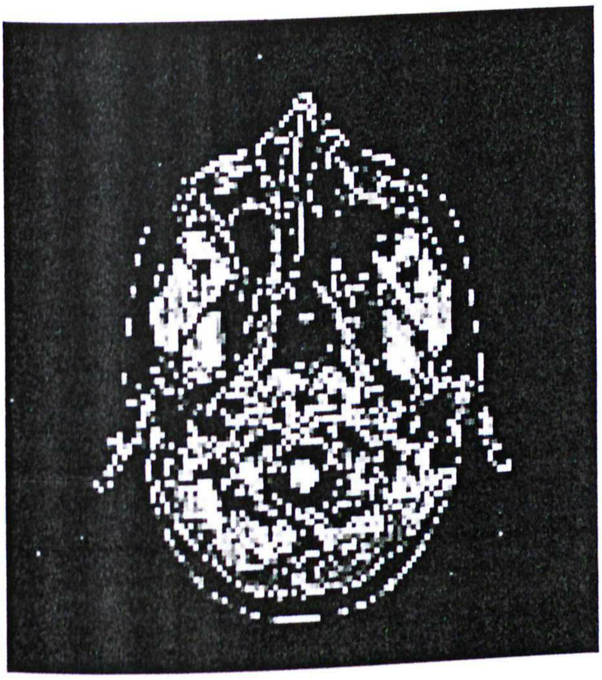
	
Title : Cluster 1	Title : Cluster 2
	
Title : Cluster 3	

Test 3

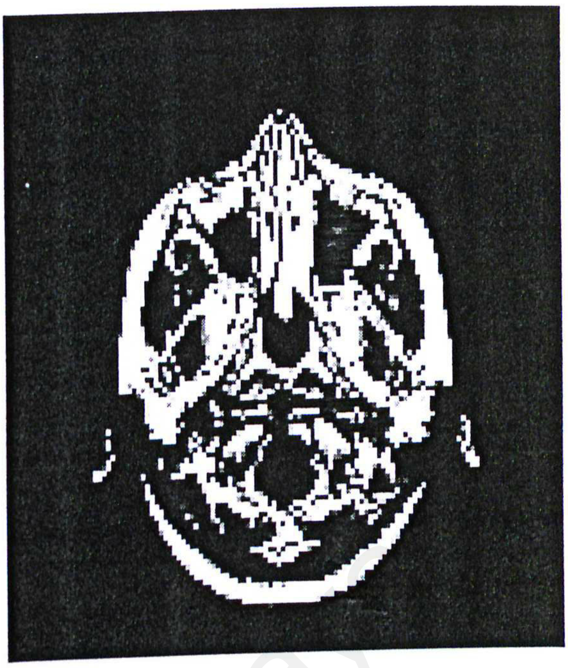
Image title : Brain MR image

Image size : 128 x 128 bits

No. cluster : 4

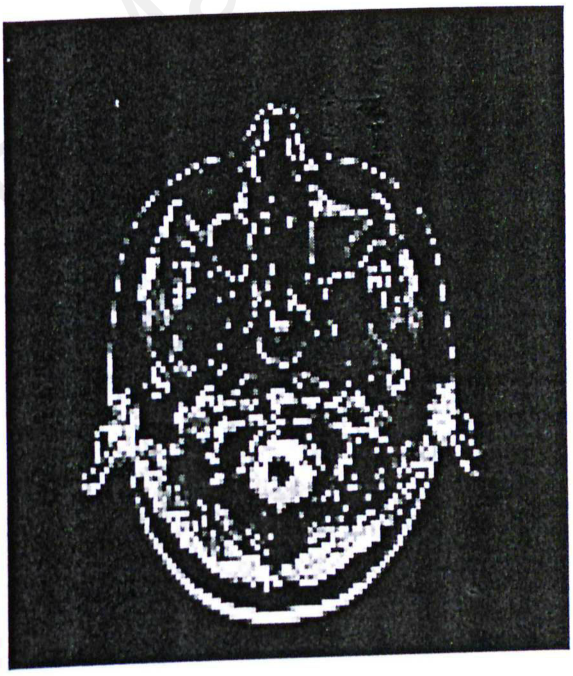


Title : Cluster 1



Title : Cluster 2

Title : Cluster 3



Title : Cluster 4

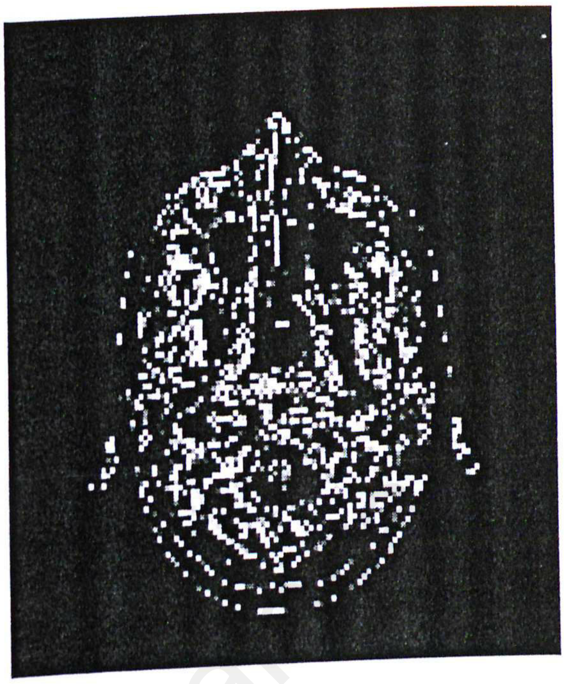
Test 4

Image title : Brain MR image

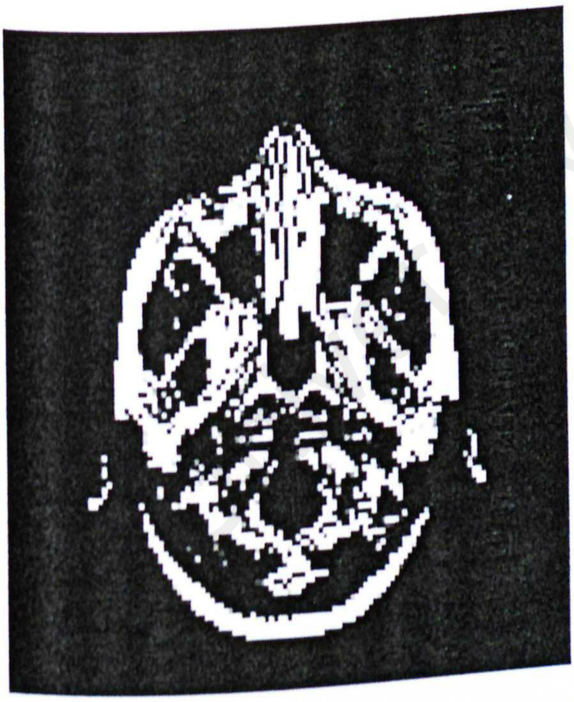
Image size : 128 x 128 bits

No. cluster : 5

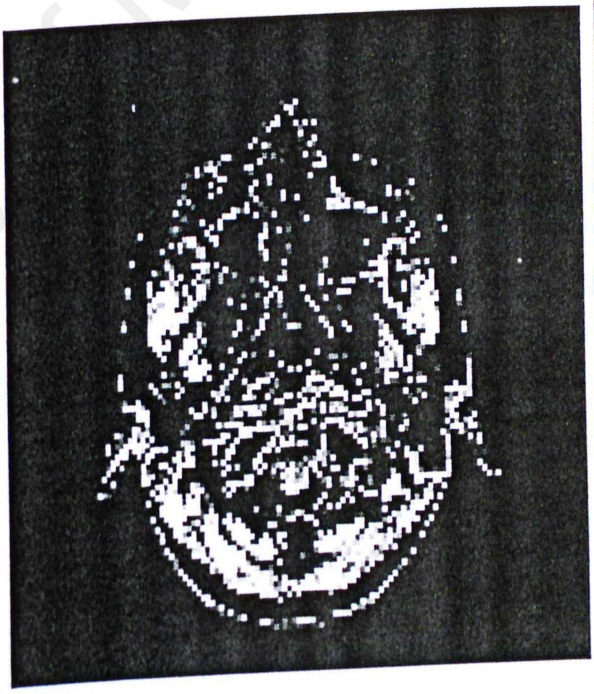
Title : Cluster 1



Title : Cluster 2



Title : Cluster 3



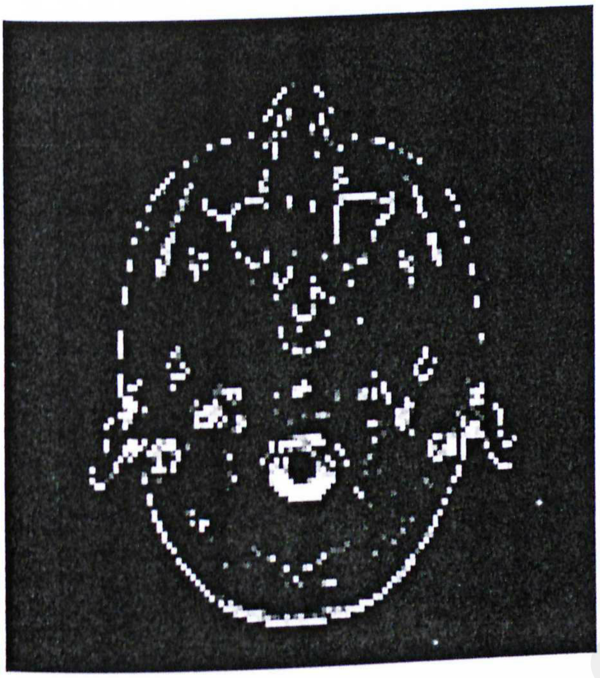
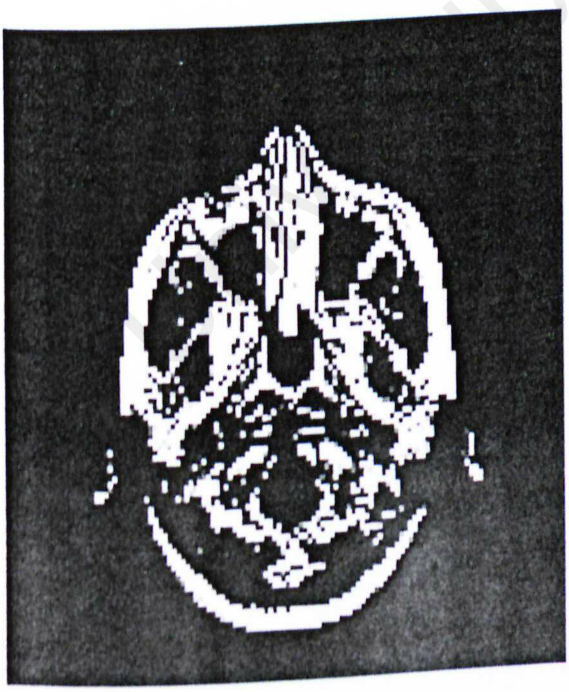
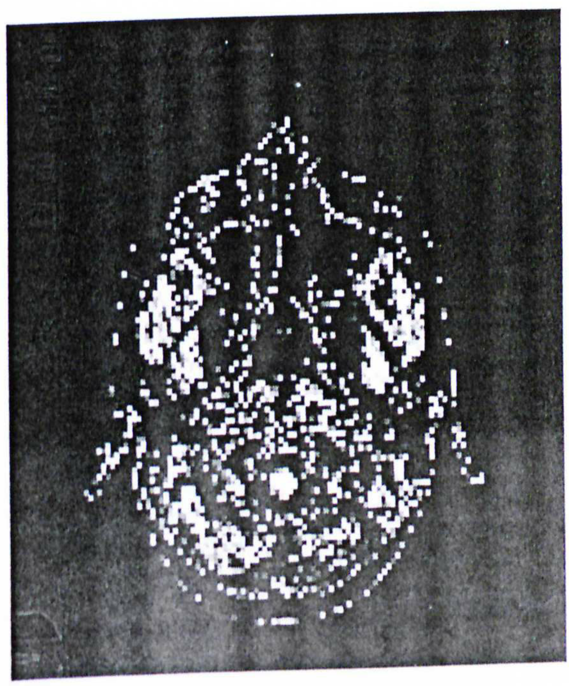
Title : Cluster 4

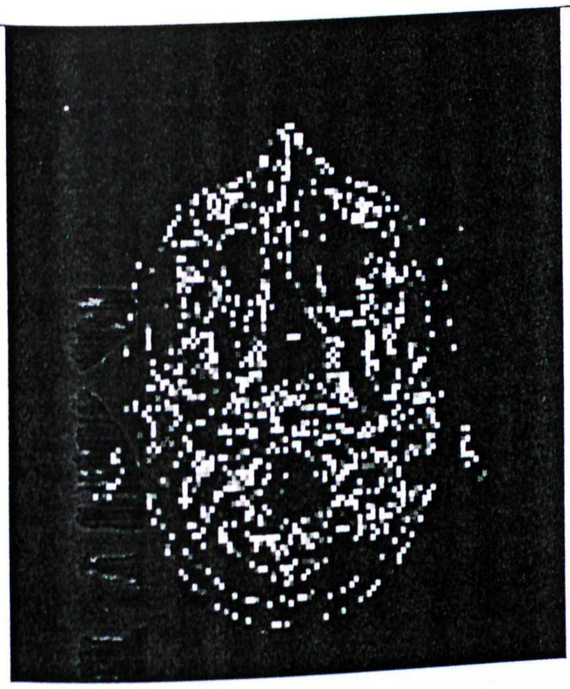
Test 5

Image title : Brain MR image

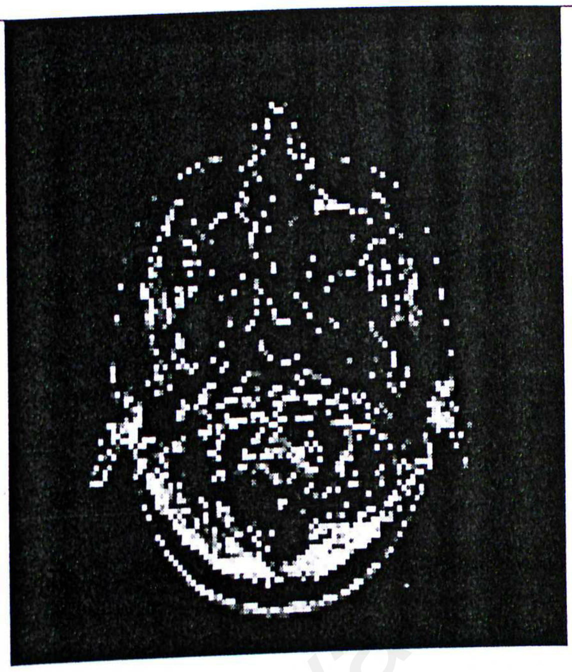
Image size : 128 x 128 bits

No. cluster : 6

	
Title : Cluster 1	Title : Cluster 2
	
Title : Cluster 3	Title : Cluster 4



Title : Cluster 5



Title : Cluster 6

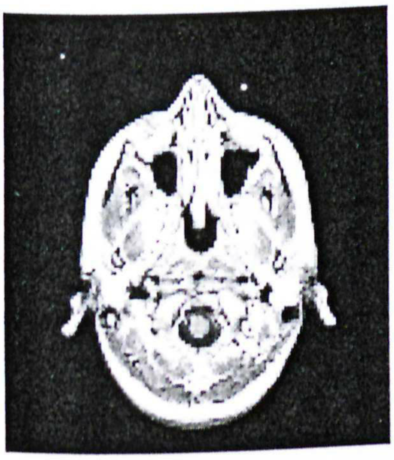
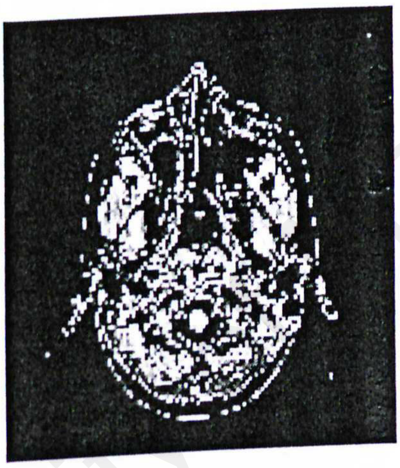
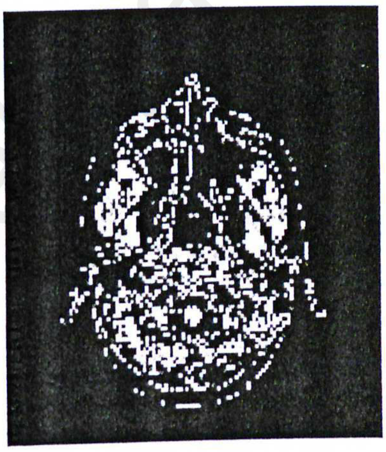
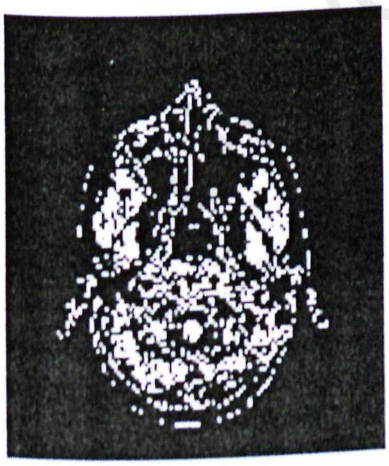
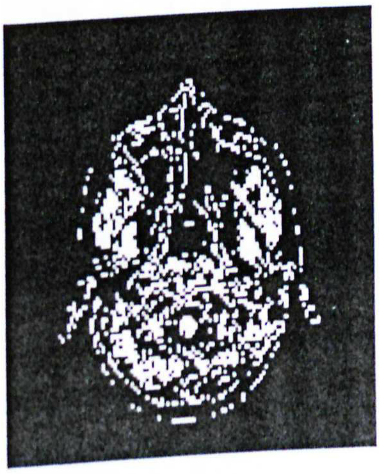
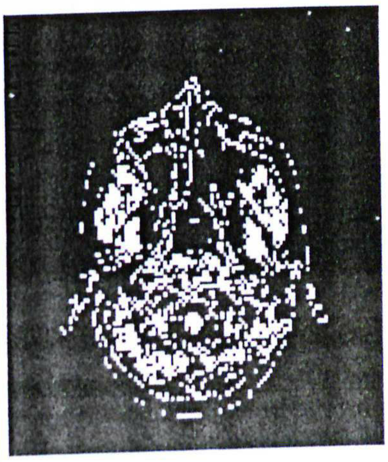
6.4.2 *System testing with a different number of epochs*

Test 1

Image title : Brain MR image

Image size : 128 x 128 bits

No. cluster : 4

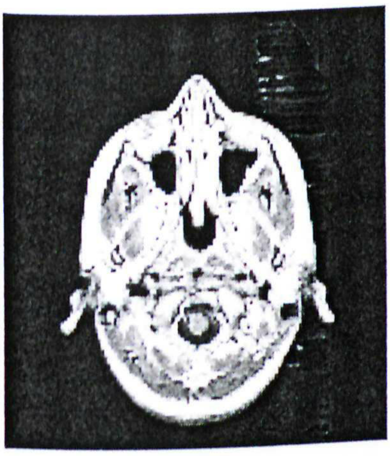
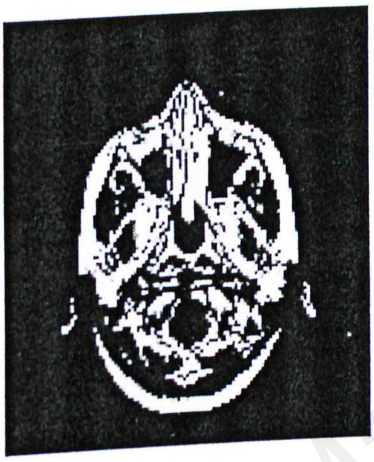
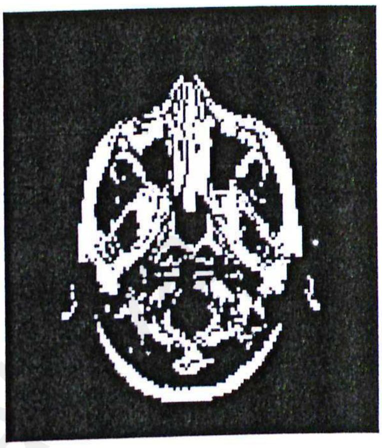
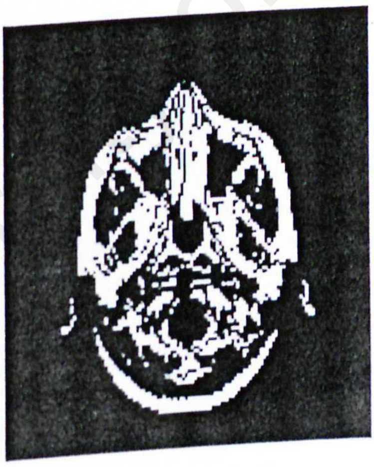
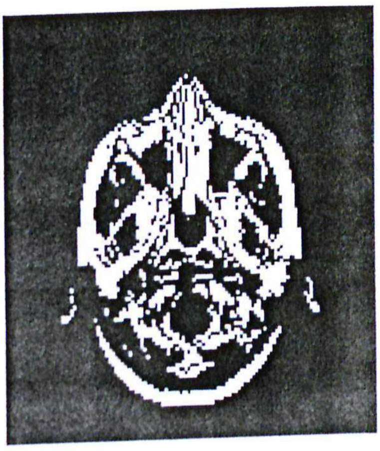
		
Title : Original image Epochs: -	Title : Cluster 1 image Epochs: -	Title : Cluster 1 image Epochs: 5
		
Title : Cluster 1 image Epochs: 10	Title : Cluster 1 image Epochs: 20	Title : Cluster 1 image Epochs: 30

Test 2

Image title : Brain MR image

Image size : 128 x 128 pixels

No. cluster : 4

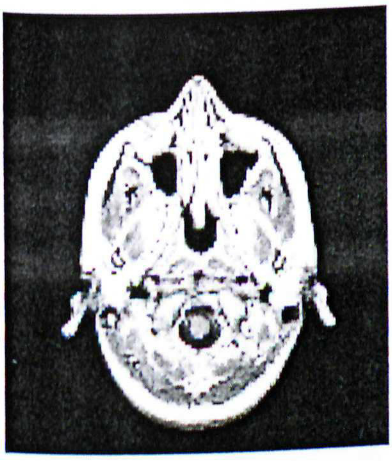
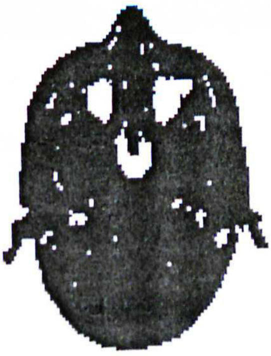
		
Title : Original image Epochs: -	Title : Cluster 2 image Epochs: -	Title : Cluster 2 image Epochs: 5
		
Title : Cluster 2 image Epochs: 10	Title : Cluster 2 image Epochs: 20	Title : Cluster 2 image Epochs: 30

Test 3

Image title : Brain MR image

Image size : 128 x 128 pixels

No. cluster : 4

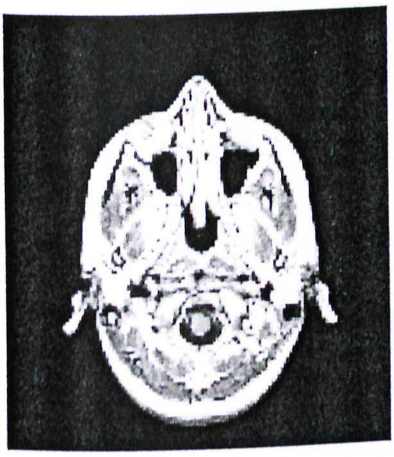
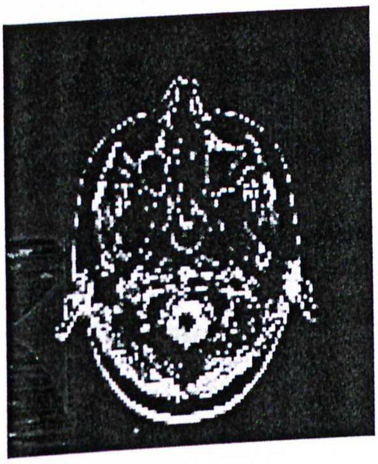
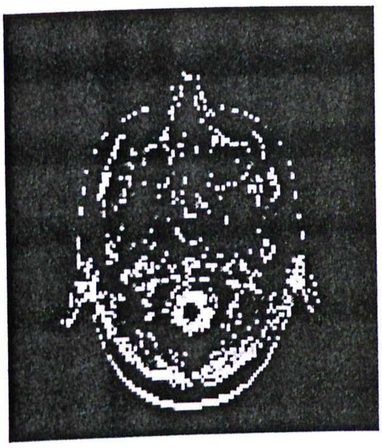
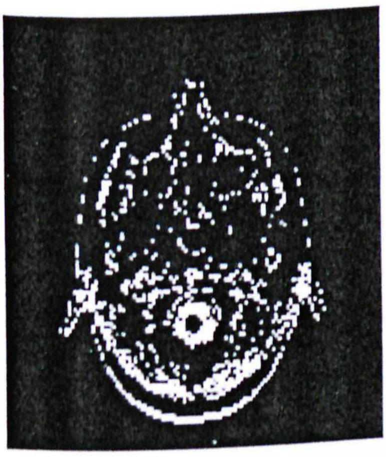
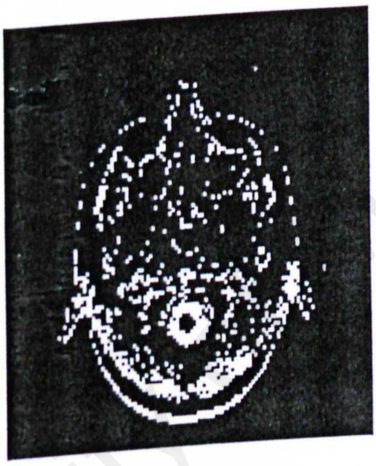
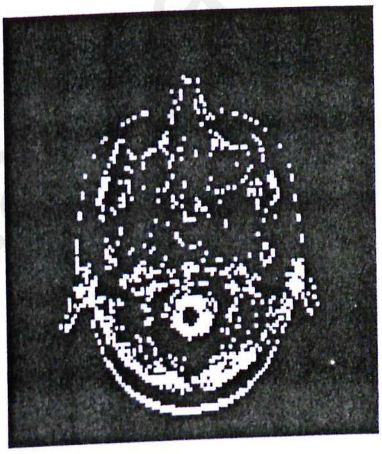
		
Title : Original image Epochs: -	Title : Cluster 3 image Epochs: -	Title : Cluster 3 image Epochs: 5
		
Title : Cluster 3 image Epochs: 10	Title : Cluster 3 image Epochs: 20	Title : Cluster 3 image Epochs: 30

Test 4

Image title : Brain MR image

Image size : 128 x 128 pixels

No. cluster : 4

		
Title : Original image Epochs: -	Title : Cluster 4 image Epochs: -	Title : Cluster 4 image Epochs: 5
		
Title : Cluster 4 image Epochs: 10	Title : Cluster 4 image Epochs: 20	Title : Cluster 4 image Epochs: 30

6.5 Test conclusion

From the testing result above, here I stated a few conclusions as follows;

1. Clustering is a pre-processing step before classification process. For each clustered image, a pixel with high degree of membership looked brighter. This bright area can be defined as a specific anatomy. Next process will classified the image into two classes.

2. The output image quality is better with incrementing the number of epochs. A stable number of epochs are 30 epochs, where the output value is 1 or –1 mean black or white. Compare to the quality of output image where the epoch number is 5, there are still a lot of pixels that not achieved to the target value 1 or –1. So we don't get the perfect segmentation part.

CHAPTER SEVEN

CONCLUSION

7.1 *Introduction*

This system is successfully work after passed a lot of problems and stages of development success. The most critical phase is at implementation to a real system based on the system design. Continuous effort is a keyword to solve all the rising problems. Here are several issues faced during a system development.

7.2 *Problems*

7.2.1 *Selecting a learning algorithm for neuro-fuzzy technique*

As we know, there are many learning algorithm for neural network. Each one has their properties and mechanism. The problem here is what is the best learning algorithm and fuzzy technique for this system. To solve this, I' am referred to the journal article on title *'Technique and comparative analysis of neural network and fuzzy system in medical image segmentation'* written by Cheng K S, Lin J S and Mao C W. This article presents a comparative analysis and briefs generally the algorithm and mechanism for each technique involve in this study. I took this paper as a theoretical reference to develop a design for this system.

7.2.2 *New in using Matlab*

Matlab is an intuitive language and a technical computing environment. It provides core mathematics and advanced graphical tools for data analysis, visualization, algorithm and application development. There are a lot of built-in functions and syntaxes to understand before we can make use of it. As mention before, Matlab provide a good reference from a big and fine organize documentation file. It can be access using a help toolbox. This toolbox is very helpful for users to apply all functions and syntaxes when coding a program. A programmer must continuously and frequently refer it for soft work.

7.2.3 *Implementing a neuro-fuzzy technique to this system*

Neuro-fuzzy is a combination of two intelligent instruments that is neural network and fuzzy logic. These two techniques work separately but needs each other. Neuro-fuzzy is not only used in digital image processing but it can be implemented in many fields of applications. This system used two important functions *fcm* from fuzzy logic toolbox and *newhop* from neural network toolbox. The problem here is how to implement these two functions in digital image processing. From experience before, first we must know how these two functions work and what is the data provided by the MR image as input. To do this we must try with a simple data as a function input and evaluate the output. After we satisfied to this simple operation then we turn to an exact input data. Finally we evaluate the output to validate the system.

7.2.4 *Takes a lot of times to process an image data*

This system takes a lot of times to process the image data. For example, to work on image in size 128 x 128 bits to 4 clusters and 30 epochs using Pentium III 667 Mhz processor with 128 Mb RAM computer system, it takes approximately 10 hours to finish the process. The most critical part in this computation step is at classification stage when the system implementing a neural network algorithm. There are many factors to look in. One of it is the number of neuron. This network only has one neuron to process a whole data. This problem must look in detail to modify the network for future enhancement.

7.3 *System Strength*

7.3.1 *Integrated intelligent technique*

The integration of neural network and fuzzy logic in one system is the biggest advantage for this system. Compare to the system where the technique implemented separately, this system gives a better output with a clear segment at a stable number of epochs. This segmented image is very useful for further analysis like 3 dimensions modeling or volume measurement.

7.3.2 *Simple coding*

A source code used to develop this system can looked clearly and simple. This is because there are a lot of built-in functions in Matlab. Example like *fcm* for fuzzy C means algorithm and *newhop* for Hopfield neural network algorithm. This property helps other programmer frank to understand and modify the source code for future enhancement.

7.4 *System limitation*

7.4.1 *No user interface*

A public user can't use this system. It doesn't have a graphical user interface. User can run this system only in Matlab environment. They must first understand how the code is running before they can use it. When users change the input data, several codes must change manually like the size of image, number of clusters, number of epochs and matrix filename as input. A fix setting for this program is an input image size is 128 x 128 bits of pixels, number of cluster is 4, number of epoch is 30 and matrix filename is matrix1.m.

7.4.2 *Cannot select a region of interest.*

Selecting a region of interest is an important pre-processing step before image segmentation process as in system design. This process is essential to reduce a noise pixel and focusing a segmentation process to anatomy of interest from the MR image. This also helps to cut down a moment process and generate a better output for visualization analysis.

7.4.3 *Running in Matlab environment*

This system only runs in Matlab environment not in execution format. To make possible user need Matlab software with a neural network toolbox and fuzzy logic toolbox. It requires a big expenditure to buy this software.

7.5 *Future improvement*

7.5.1 *Builds a user friendly interface*

This system is very valuable in medical image analysis. A public user like radiologist, doctors, teachers, and other who are related to anatomical field can use it. A modification process must be done to help user access to this program from a graphical user interface in execution format and not in Matlab format. It also helps to growth the flexibility of the system.

7.5.2 *Modify the network structure*

As mentioned before, this system takes a lot of times to process a small MR image. For future improvement, programmer must add the number of neuron to the network structure for parallel processing.

7.5.3 *Expand to 3D modeling function*

Image segmentation is a pre-processing step before 3D modeling. We can expand this system to 3D modeling function. A 3 dimensional visualization of anatomy is every useful aid for health care treatment and education purpose. Here are a few examples of 3D modeling applications used in today;

1. Diagnostic: Diagnosis of multiple sclerosis.
2. Surgery planning: Cracial facial surgery
3. Traumatology : Pelvis surgery
4. Radiotherapy planning: Tumor enhancement monitoring
5. Implant design: Femur bone implantation
6. Quantification of tissue volume: Tumor diagnostic
7. Robotic surgery: Microbot to remove cancer cells
8. Bio-modeling: Modeling anatomy of interest
9. Medical research and education: Interactive exploration of detailed 3D anatomical model.

7.5.4 *Add function to select a region of interest*

This system must let user to select a region of interest from the MR image. This helps to cut noise and decrease a moment for image processing.

7.5.5 *Build a systematic database*

All images have the identity and go to a person. A database can help user to arrange systematically the identity of person who is fit in to the image. A database also can store the analysis information from the image like tumor volume, date the picture is taken, gender of patient and other important information considered necessary.

Lastly in my view, this project got achieved all objectives stated at the early chapter that are;

1. To study about segmentation process using neuro-fuzzy technique on MR imaging data set.
2. To segment and model the specific human anatomy of interest from transverse MR images.
3. To use a neuro-fuzzy technique in segmentation process.

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